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Personal Energy Administration Kiosk application:
an ICT-ecosystem for Energy Savings
through Behavioural Change, Flexible Tariffs, and Fun
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Deliverable 5.2
Analyzing the impact of dynamic electricity prices on the Austrian energy system

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Content

1 Introduction

1.1 Background

In the context of the transition to more sustainable energy systems, fundamental structural changes are currently underway. The focus is thereby on the decarbonization of the energy system, through a combination of energy efficiency/demand reduction and the exploitation of renewable energy supply technologies. The latter are being widely developed, including both dispatchable hydro-power and bio-energy and non-dispatchable wind and solar technologies. The continued exploitation of wind and solar energy technologies depends on technical and economic measures to integrate them into the energy system. The measures include but are not limited to extending and densifying existing networks, operating existing (e.g. thermal) power plants more flexibly, increasing storage capacities, sector coupling between power/heat/transport/gas systems, and exploiting smart grid approaches to more strongly and automatically connect the many disperse actors and technologies in the energy system. An additional measure involves exploiting the flexibility on the demand side of the energy system in the context of Demand Side Management (DSM). The idea of doing this has existed for several decades, but recently more attention has been paid to exploiting this approach in the residential sector. Residential consumers are typically not exposed to short-term price differentials, instead the majority pay a constant price per unit of electricity consumed. To exploit the apparent potential for demand flexibility in the residential sector, however, consumers need to be exposed to fluctuations in electricity prices already seen on wholesale markets. The eponymous PEAKapp developed within the same project attempts to do this, by giving users the ability to change their short term behaviour in response to changing electricity prices. The app creates an incentive, in the form of lower energy costs, for consumers to adapt their behaviour to be more economically efficient and system-serving. The realisable potential of households to shift loads off the peak times to periods with lower consumption can have effects on the market price and distribution costs for electricity, and thus stands to make renewable electricity more competitive.

1.2 Methodology and objectives

Within the PEAKapp project, Task 5.2 assessed the extent of these positive effects in the scenario of a wide-spread application of the information and communication technology (ICT) to Human ecosystem. Two field trials were carried out in the project, which involved a large-scale roll-out of the PEAKapp alongside control groups in Austria and Estonia. In this Deliverable we focus on the Austrian field study, which involved around 1600 participants over a period of about 18 months. The thorough analysis of the field trial data was carried out by JKU, DTU and Tecnalia and is documented in Deliverable D.4.1. One aspect of this analysis involved deriving short-run price elasticities for the households participating in the trial. These elasticities are employed within this report in order to analyze the responsiveness of households to future changes in electricity prices under different framework conditions. To this end we employ an energy system model (Balmorel) that allows a comparative static analysis of the electricity market equilibrium, assuming different aggregated consumption profiles under alternative pricing regimes. The overall objective thereby is to analyse the economic benefits to the whole (Austrian) energy system of exploiting residential demand side flexibilities at the national scale. More specifically, the objective is to analyze the impact on economic, technical and environmental indicators of a widespread exploitation of demand side flexibility.

The method employs the existing linear optimization energy system model Balmorel, which is extended to cover Austria in the given context. It thereby employs the price elasticities mentioned above as an exogenous input to derive changes in an exogenous demand in the residential sector. The analysis is carried out for the timeframe to 2030 within a scenario framework of four scenarios. These include a Business As Usual (BAU) and Renewable Scenario (REN), in both of which the demand is assumed to be inelastic. Two additional variants of the renewable scenario consider these elasticities and therefore have flexible demands, whereby we distinguish between active and passive flexibilities. Active implies load shifting on behalf of the participant, and in this context means having the PEAKapp and using it. Passive on the other hand means either not having the PEAKapp, or having it but not using it. By comparing these four scenarios in terms of diverse economic, technical and environmental criteria, we are able to explore the system level impact of PEAKapp in Austria. The novelty of the method lies in the approach to consider the flexible demand (Section 3.2) as well as the application to the Austrian energy system. The findings show that the elasticities can potentially lower fuel consumption and electricity demands, promote investments in renewable technologies and lower total system costs when striving for a carbon-neutral energy system.

1.3 Overview

This report is structured as follows. Section 2 contains a literature review, which puts this work into context and demonstrates the innovative aspects. Section 3 then presents the methodology, including the Balmorel model, the model extension to Austria, the modelling of elasticities and the scenario framework. Section 4 then presents the main results, which are organised according to the above technical, economic and environmental criteria. Section 5 discusses the results, the methods employed and highlights avenues for further work. The report closes in section 6 with a summary and conclusions.

2 Literature review

This section presents an overview of previous studies of energy-system effects of electricity demand flexibility (EDF), using Balmorel among other models. It is described in ten subsections: literature search, type of model, geographical coverage, sector coverage, type of flexibility and how it was realised, source of energy demand data, scenarios, time resolution and time scale, claim of novelty and results.

Literature search

From the research ten published studies deemed suitable for this review were identified. The search for the documents was carried out first through a Google search for articles, which contained one or more of the following keywords: Demand Response, Residential Sector, Balmorel. Balmorel was included as a keyword because it is the energy system model chosen for the present study. Secondly, further articles that were cited by the ones found through the keywords search were identified. In the end, only the most relevant articles were selected, resulting in a total of ten articles.

The review focused on the scope and methodology applied by the studies, as well as the studies' claim of novelty, summarised in Tables 1 to 4 below.

Type of model

Seven of the reviewed studies applied an actual energy system model, of which five applied the model (Balmorel) used in this study, and two applied similar system-wide models (TIMES for the UK [1], and KAPSARC for Saudi Arabia [2]). All seven models are technologically detailed optimization models that select technologies to minimize overall system costs while meeting the energy demand. One study applied a partial equilibrium model (also minimizing system costs)[3], while the remaining two studies used models/algorithms at a household level.

Geographical coverage

For the seven studies using energy system models, the geographical coverage ranged from the supra-national (Balmorel) to the country level (Balmorel, TIMES and KAPSARC). Six of these studies concerned Northern Europe including the Baltic countries, and one Saudi Arabia. This geographical bias is due to fact that the model used in the present study, Balmorel, was originally developed for Northern Europe (see [4]). The three studies using other types of models concerned Denmark [3], Finland [5] and Latvia [6], respectively.

Sectoral coverage

Six studies specifically target the household/residential sector, while the study by Li and Pye (2018) [1] also includes the transport sector in the form of electric vehicles. The study by Grohnheit and Klavs (2000) [7] concerns electricity demand for the residential as well as the service and industrial sectors, while the studies by Jensen et al (2000) [8] and Tveten et al (2016) [9] covers the whole power and CHP market. It should be noted that all five studies using the Balmorel model by default cover the power and CHP market in terms of the system-wide effects, even of the analysis of demand response is focused on a particular sector (e.g. households, services or industry).

Type of flexibility and how realised

The reviewed studies analysed demand response as a flexibility resource in the form of load shifting (reducing demand at a given price level) or peak clipping (reducing peak demand where the demand appears later on), or both, for either electricity only or for both electricity and heat. Five studies had an explicit focus on household appliances as a source of flexibility and one of these studies further assessed the flexibility potential of electric vehicle charging. In two of the five studies (Li and Pye 2018 [1], Mishra et al 2016 [10]), were the appliances actually, or assumed to be, automatically controlled, while the other studies were unspecific on this point. All studies concerned short-term (intra-day) flexibility, typically 1-6 hours, which is also the approximate time scale of the PEAKapp intervention. Not all studies specified the exact time-scale for flexible demand response. However, few of the studies report on original experimental data on flexible demand response but rely on secondary data.

Source of energy demand data

Three studies (Li and Pye 2018 [1], Mishra et al 2016 [10], Lacaine et al 2015 [6]) use experimental data on energy consumption (using smart meters recording consumption at an hourly (or finer) interval as inputs to the modelling of system-wide effects. One study (Ali et al 2015 [5]) generated heat load profile data for a typical Finnish household from a building energy consumption-modelling tool, while the remainder studies rely on data from national databases, the Nordpool electricity market, the literature. The study by Matar (2017) [2] did not specify the exact data source.

Scenarios

Six studies developed scenarios simulating different levels or types of demand-side flexibility. In the study by Katz et al (2016b) [3], the scenarios simulate different levels of wind power in final consumption, while the two scenarios in Mishra et al (2016) [10] simulate a system with grid connection ('market') and one without grid connection ('island'), i.e. where the grid connection is a flexibility mechanism.

Time resolution and time scale

The analyses of demand response were based on load profiles with a resolution of one hour (sometimes less) and covering a period from 1 week (Jensen et al 2006 [8]) to 1 year (e.g. Lacaine et al 2015 [6], Katz et al 2016b). The study by Katz et al (2016b) [3] focuses on the time of day with the greatest load shift potential for household appliances, i.e. the evening (shift from 16:00-19:00 to 20:00-23:00). Lacaine et al (2015) [6] selected both morning (05:00 - 08.00) and evening (17:00 - 21:00) as peak times. Regarding the time scale of the scenarios, only three studies applied scenarios over longer periods, namely up to 2030 (Tveten et al 2016 [9]), 2035 (Katz et al 2016a [11]) and 2050 (Li and Pye 2018 [1]).

Claim of novelty

The claims of novelty in the reviewed studies centre on the ability to reliably assess the system-wide effects of demand-side flexibility (DSF) at household level, regarding especially overall system costs, consumer and producer benefits, and the integration of low-carbon energy technologies (especially wind power). The wide range of methodologies applied and assumptions made in the reviewed studies, even for those using the same energy system model, suggests that this is a relatively young and dynamic area of research.

Results

In general, the economic benefits of demand-side flexibility (DSF) for electricity producers (especially variable renewable resources) are larger than for the consumers, suggesting that there are distributional issues associated with DSF as well as weak household incentives to adopt flexible consumption. One study (Katz et al 2016a [11]) compares intra-hour and intra-day demand-side flexibility, corresponding to consumer participation in, respectively, hourly spot (balancing) and reserve markets. It concludes that consumers can gain most by participating in reserve markets where price differences are larger. Intra-day is the type of flexibility emphasized by the PEAKapp project. Most studies identify significant system-level benefits of household DSF, including lower overall system costs, less need for energy storage, higher shares of renewable energy, and lower carbon emissions. Hence, renewable electricity producers as well as society as whole have an interest in promoting greater demand-side flexibility among consumers. However, presently the latter have neither strong economic incentives nor effective (smart) technologies installed to be flexible.

Reference	General approach	Model used	Geographical coverage	Type of flexibility	How flexibility was realized	Source of energy demand data
Katz et al (2016a) [3]	Optimization	Balmorel	Denmark	Load-shift horizon of 4 hours	Analysing the usage of different appliances, as opposed to the abstract concept of price elasticity.	Assumptions about demand response is based on values found in the literature
Mishra et al (2016) [10]	Optimization	Balmorel	Estonia	Peak clipping and shifting (flexibility assessment was done by estimating which appliance power usage could be shifted considering human behaviour)	Automatic (data was collected from a 3-room apartment with 95% accuracy in comparison with the standard energy meter)	Demand profile is altered by flexible appliances. Energy consumption data from direct measurement by smart meter in one household.
Jensen et al (2006) [8]	Meta-modelling approach (power market models are combined with a Monte Carlo analysis)	Balmorel	Nordic countries	Peak clipping and load shifting	Fixed in each scenario, i.e. the amount of load shift or peak clipping one can do	Their distributions were assessed based on statistical Nordic data from a long time series. The programme Crystal Ball was used to draw the 100 simulations of varied input.
Matar (2017) [2]	Optimization	- Internal bottom-up models developed for residential sector -KAPSARC Energy Model	Saudi Arabia	Electricity load shifting for appliances and air-conditioners	Households can respond to price changes in two ways: they can alter their thermostat set-point or shift the discretionary use of appliances.	Electricity prices from 2011 for Saudi Arabia, not specifying the data source. Two examples of pricing schemes are time-of-use tariffs and real-time pricing. Electricity and Co-generation Regulatory Authority. Electricity Tariff (2011).
Ali et al (2015) [5]	Optimization. Two-stage model for consumer participation in power market: 1) day-ahead power market (24 hr); 2) balancing power market (1 hr)	- Hourly heat load profiles are generated using IDA - CPLEX solver in GAMS	Finland	Price based demand response (storage space heating system with flexible charging capability)	Communication infrastructure and smart meter.	Nordpool: A typical hourly time varying prices are selected for Stage 1 scheduling which is retrieved from Nordpool
Li and Pye (2018) [1]	Optimization	TIMES-UK	The UK	Some equations were introduced into the existing TIMES model to regulate DR of smart appliances and EVs	Smart controlled appliances and passenger EVs	Charging profile of passenger EVs is based on the trial results conducted in Low Carbon London. Appliance usage data based on secondary sources.

Table 1: Table 1, Part A. Methodologies used in studies of energy system effects if demand response

Reference	General approach	Model used	Geographical coverage	Type of flexibility	How flexibility was realized	Source of energy demand data
Grohnheit and Klavs (2000) [7]	Optimization	Balmorel	Baltic Sea Region	Price and income elasticities for electricity and heat consumption in different economic sectors /customers. Type of flexibility is not specified.	Not specified (elasticities are given for each sector).	National statistical data. Estimated either by econometric methods from time-series or cross section analyses, or they are calibrated within a model framework.
Tveten et al (2016) [9]	Optimization	Balmorel	Germany, UK, Netherlands, Nordic countries	Load shifting, by assuming that a certain share of the demand may be shifted from one hour to another on a diurnal basis.	We model demand-side flexibility (DSF) by adding a variable representing an hourly shift in demand (Dd1(r,s,t)) to the energy balance, where Ddr,s,t can have a positive or a negative value, depending on whether there is an upwards or downwards shift in demand. The system optimal DSF is determined endogenously based on the potential. Future DSF potentials are associated with a high degree of uncertainty. We analyse DSF in the form of within-day load shifting, by assuming that a certain share of the demand may be shifted from one hour to another on a diurnal basis.	Literature
Katz et al (2016b) [11]	Partial equilibrium modelling	Closed-market model.	Denmark	Load shift	Fixed in each scenario, i.e. the amount of load shift or peak clipping that you can do.	Literature
Lacaine et al (2015) [6]	Household electricity demand model	Algorithm	Latvia	Load shifting. A washing machine and a dishwasher - were selected for assessing the potential for load shifting	Smart metering / Time of use surveys	Empirical measurement of load shifting.

Table 2: Table 1, Part A1. Methodologies used in studies of energy system effects if demand response

Reference	Scenarios	Sector	Number of households	Time scale	Claim of novelty and results
Katz et al (2016a) [3]	Five scenarios: - Reference: Neither reserve requirement nor flexible demand; - Reference flex: Flexible demand, but without reserve requirement; - Base case: Reserve requirement, without flexible demand; - Spot: Reserve requirement, with flexible demand included in the energy balance equation; - Reserve: Reserve requirement, with flexible demand included in the energy and capacity balance equations.	Residential households	Not applicable	2035	Able to determine a first estimate of the system value that demand flexibility may contribute with by households participating in hourly spot and reserve markets. While attractiveness of the price differences in hourly spot markets may be limited, participation in reserve markets may provide an additional source of income to providers of flexibility on the demand side.
Mishra et al (2016) [10]	Two scenarios: 1) The simulated area is grid connected and a motivator for the area to change the consumption of appliances; the electricity market price is fed for the area as an external influence; 2) The island scenario assumes a disconnected island operation of the area that allows investments in solar PV panels, wind turbines and diesel generators.	Households	100 households	1 year (52 weeks with 168 weekly hours)	The study exhibits the scope of demand-side flexibility in cost efficient integration of power from intermittent renewable sources that results in efficient fuel economy. Results indicate an overall increase in the efficiency of energy consumption with a demand-shifting possibility. DSM is an efficient way to modify the demand patterns in order to suit the needs of power systems.
Jensen et al (2006) [8]	Five scenarios: - Reference: Load disconnected at value of lost load (assumed to be 5000 NOK/MWh) - DR1 (PC): Peak clipping of 1,000 MW in South Norway disconnecting at 1000 NOK/MWh - DR2 (LS-DK): Load shifting of 1000 MW in Western Denmark - DR3 (LS-NO): Load shifting of 1,000 MW in Southern Norway - GT: Additional 1,000 MW of gas turbines.	Not specified. The sectors are the ones in Balmorel, i.e. power and CHP.	Not applicable	1 week (winter 2010) at 1-hour time resolution.	The system will benefit in all scenarios. As an option, the peak-clipping scenario is superior as the value of load shifting in a system with large amounts of hydropower is limited. A large proportion of the total benefit was obtained in only a few cases. Since the benefit is low in most cases, industry players might not see the importance of demand response. The revenue stream will also be unreliable.
Matar (2017) [2]	Two scenarios: - Appliance load shifting in response to a price change; - Adjusting the thermostat in response to a price change.	Households	Not applicable	One year (2011)	Quantify how households may react to a price change (Time of Use pricing) by focusing on two of the biggest electricity consuming items: appliances and air-conditioners. Price response features that deal with the usage of these items are incorporated in a modelling framework. The power sector enjoys an overall profit gain due to higher residential prices in the summer. The majority of the gain stems from the higher revenues from residential customers. The utilities may also benefit form a lower cost of operation, which also results in a lower use of crude oil.

Table 3: Table 1, Part B. Methodologies used in studies of energy system effects if demand response

Reference	Scenarios	Sector	Number of households	Time scale	Claim of novelty and results
Ali et al (2015) [5]	Two case studies were simulated: (1) Optimization of heat load management using entire storage heating unit flexibility in Stage 1. (2) Optimize the heat load scheduling in Stage 1 vs maintaining some flexibility for Stage 2. Seven different scenarios were generated, based on the two cases and different time-of-day bonus incentive levels.	Residential	One domestic household	1-hour time resolution of load.	A realization of domestic storage space heating demand response (DR) capability in balancing market allows the customers to make savings in energy expenses as well as the system operator to benefit from DR.
Li and Pye (2018) [1]	Two scenarios without and with demand-side response in households. The scenarios have same GHG targets: reducing emissions by 80% relative to 1990 and the five UK carbon budgets, including a 57% reduction by 2030.	Residential and transport sector (EV)	Not applicable	2010 - 2050	A novel modelling approach in a whole energy systems model, to investigate the benefits of demand-side flexibility from smart appliances and EVs. Demand-side control increases system flexibility, enabling the integration of high levels of low-carbon power, whilst reducing the requirements for storage.
Grohnheit and Klavs (2000) [7]	The study does not report on scenarios but refers to another article (Varming et al. 2000)	Residential, Service, Industry	Not applicable	Not specified	The key parameters in this further model development are partial price elasticities for electricity and heat at sectoral or aggregate levels. The paper discusses the possible numerical values of these parameters and their implementation in the Balmorel model.
Tveten et al (2016) [9]	Three scenarios: - Baseline scenario, assuming no demand-side flexibility (DSF); - Moderate DSF scenario, assuming a 50% realization of the maximum potential; - Full DSF scenario, where the total potential is assumed implemented.	Power markets	Not applicable	2030	Producers' revenues for VRE technologies increase for all types and locations of VRE generation when demand-side flexibility increases, with the most significant increase in revenues found for wind power. System benefits - in terms of reduced residual demand levels, reduced need for peak capacity, and increased security of supply - are larger than the consumer benefits.
Katz et al (2016b) [11]	Two scenarios: - Base wind: applies an hourly profile of the wind share in consumption in 2012. - High wind: share of consumption increased up to 50%.	Households	Not applicable	Scenario: Hourly profile of wind in 2012 (DK) Demand side: DK consumption profile of 2012. Retail pricing: Shift volumes relative to a time window of 3 hours. Cases cover early and later evening.	An approach based on economic equilibrium modelling to account for the dynamic market impacts of demand response. The impact on prices and generation capacities has been a key argument in favor of demand response. Energy system studies have analyzed the long-term interaction of renewable energies with demand flexibility, but they assume optimal response to real-time system prices and do not consider retail product structures. This is where we set in with this paper, also taking a long-term perspective. Key results: 1) Simple pricing schemes could become important in an early phase to initialize the development of household demand response. 2) Demand response under variable pricing makes wind power more valuable.
Lacaine et al (2015) [6]	No scenarios. Effect on aggregate load of load shifting is assessed for different appliances and seasons - Washing machine (winter), Washing machine (summer), Dishwasher (summer)	Households	A 4-person family household	One year: April 2013 - March 2014	By increasing customer awareness and participation in demand management, it is possible to spur demand side flexibility much more effectively.

Table 4: Table 1, Part B1. Methodologies used in studies of energy system effects if demand response

3 Methodology

This section provides an overview of the applied methods and tools to implement the elasticities in the context of an energy system analysis. In Section 3.1 the energy system framework Balmorel is introduced. Section 3.2 explains the detailed approach of the introduction of elasticities within this research project. Further on, Section 3.3 highlights the employed data in Balmorel and finally, Section 3.4 explains the four different scenarios that are analyzed.

3.1 Introduction to Balmorel

Balmorel (BALtic Model Of Regional Electricity Liberalized) is an open-source, bottom-up, partial equilibrium model that employs linear programming, originally developed by Hans Ravn et al. in 2001 [12] and subsequently further extended and employed in many national and international applications [13]. In [12] the mathematical model and basic equations are described. The source code is written in GAMS (General Algebraic Modeling System) and the model is solved using a CPLEX solver with the concurrent LPmethod 6 and -1 for the number of threads (for details see the GAMS solver manuals [14]).

The Balmorel model [12] simulates investment and operations of a combined Electricity and District Heating system in an international context, whilst minimizing an objective total cost function including investment in new generation plants, operational costs and in some cases additional transmission line capacities. The model is designed to meet the energy demand within a selected time horizon for the selected countries. Electricity and heat are supplied by generation technologies such as variable renewables (solar, hydro and wind), thermal power plants (extraction and back-pressure), electrical and fuel boilers and heat pumps, as well as storage (electricity and heat). Electricity transmission between regions is constrained by available capacities, while distribution of electricity and heat are specified by losses and costs.

In the Balmorel model, the starting point is the exogenously-defined demand for electricity and heat, which are provided as inputs alongside macroeconomic developments in energy and carbon prices. The model meets these predefined demands by employing existing generation technologies, as long as technically (due to still being operational) and/or economically feasible, alongside new generation plants. Therefore, the model optimizes long-term investments over several decades and short-term energy system dispatch throughout the year on an hourly basis. Energy balance constraints ensure that energy supply and storage equals the demand in every time slice and geographical location. The supply side consists of various generation technologies, whose planned capacity, commissioning and decommissioning are defined exogenously [15]. In addition, the supply side could have endogenous capacity investments in new technologies, for example based on known power plant/network development plans or to represent energy-political transition pathways.

The Balmorel core structure is shown below in Figure 1. On the left hand side, the primary fuel consumption is found. In the middle, the energy conversions and storage are represented with their respectively energy flows. On the right side of the figure, the exogenous demand (heat and power) is shown. All technologies and flows are mathematically represented within the model, whereby any given technology most likely has several variants depending on its techno-economic specifications, and the flows are typically region-specific (Figure 2). The system boundary applies to the shown energy flows as well as their respective costs - hence imported energy carriers are associated with an annual cost and profile (which may be null in the case of renewable energy carriers), and exported energy carriers also have a marginal cost profile to meet the demand. Hence the equilibrium condition provides energy commodity prices for all geographical locations and time segments [13].

The optimal solution is found along with associated dual variables, or shadow prices, and it is obtained by application of solvers for which the principles and properties of the obtained solution are part of the standard repertoire [16].

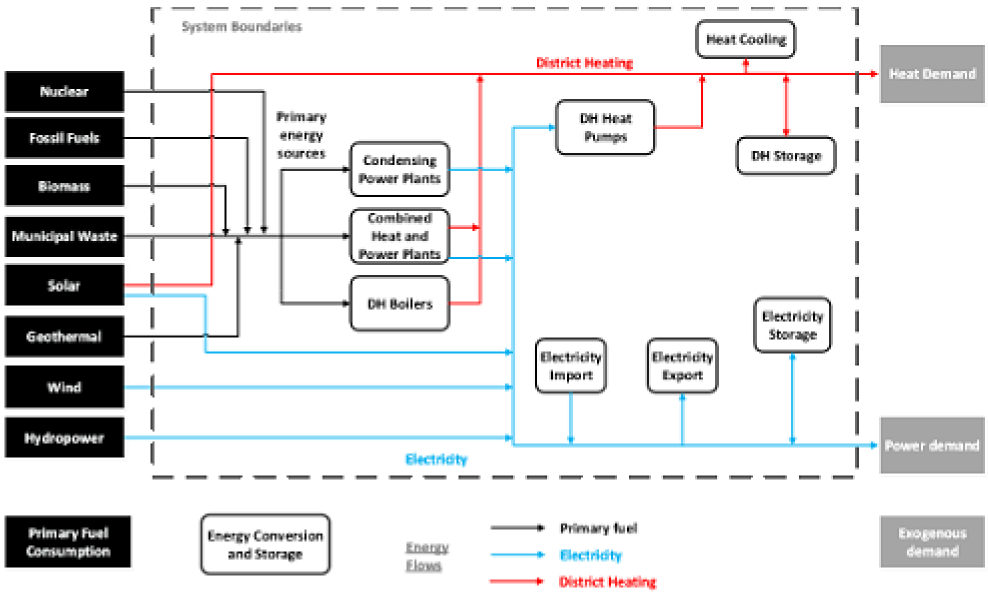

Figure 1: Schematic of the Balmorel core structure, with key inputs, transformation, storage technologies and flows

Geographically, the model is divided into three categories: countries, regions and areas. Each country is divided into a number of regions and the regions are divided into areas. Regions allow electric power transmission via inter-connectors between each other. In the areas the heat demand of each is balanced by district heating. Figure 2 shows the geographical structure of the Balmorel model.

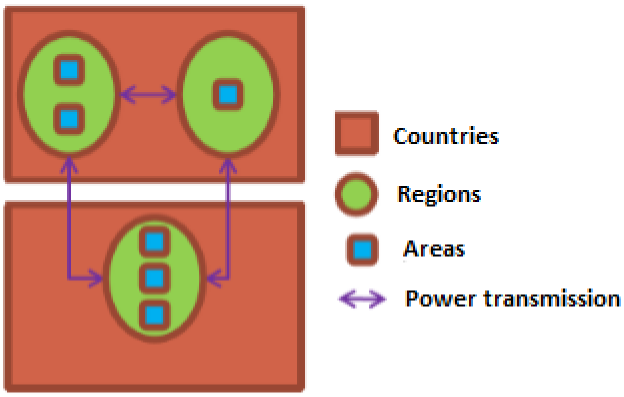

Figure 2: Abstract illustration of the Balmorel geographical structure

The model base algorithm employed is called BALBASE4 (BB4) [12]. There are currently four base models utilized in Balmorel. The version BB4 allows for solving a sequence of years with simultaneous endogenous investments dealing with a rolling planning horizon. The purpose of the add-on BB4 is to permit a model with endogenous investments that treats two or more years in an integrated fashion, whereby obtaining a limited foresight for investment decisions.

3.2 Method to consider price elasticities with Balmorel

Elasticity type

The PEAKapp field trial provided hourly point elasticities of 1600 Austrian households that were derived by using the smart meter data measuring the individual electricity consumption in 15-minute intervals. Thereby, the short-term price elasticity of electricity demand was estimated. Consumption only from primary meters was included in this analysis, so that secondary meters, mostly those that govern heat pumps and automated systems, were not included here. This is because households are generally unable to interact with the devices linked to secondary meters, and thus cannot change the consumption on these meters in response to price.

The data were cleaned to remove readings that were obviously faulty, such as meters that never registered a positive consumption value, or readings that were unrealistically high. Households in the study have various electricity tariffs (pricing plans) that they could choose. Some of these tariffs are based on a price schedule and thus vary throughout the times of the day while other tariffs do not. Through this variation in tariff levels we can identify the price elasticity of electricity demand.

In this Deliverable we distinguish two groups: those with and without the PEAKapp application, called active (EA) and passive (EP) respectively. Specifically, consumption observations are sorted into the active group if the household had access to PEAKapp during the specific 15-minute interval and are otherwise sorted into the passive group. The passive group is equivalent to the PEAKapp experimental control group described in D4.1, which consists of a randomly selected 500 households who were not given access to the app. This post-recruitment randomization should reduce the potential for sample selection bias to drive any differences in elasticities between groups.

This is monitored by the application provided to the participants by the PEAKapp consortium. The elasticities are an estimation of the willingness to change the hourly household's electricity consumption in response to a change in price, i.e. a percentage change in demand over a percentage change in price.

The empirical strategy employed here is panel data estimation and follows those of prominent papers estimating price elasticities and treatment effects on residential electricity consumption [17, 18, 19]. Specifically we estimate variants of the model where the dependent variable is the natural logarithm of the total household electricity consumption for each household and 15-minute interval.

There are a few things to note about the elasticities at this stage. Elasticities are estimated using all of the participants in PEAKapp, some of whom had the time-variant electricity tariffs, and some of whom do not. Also one third of participants do not have the PEAKapp, so their knowledge of the electricity price may be low. Households with more electricity price information and feedback are expected to be more responsive to prices, which means the selection of households for this analysis is highly relevant. But it is reasonable to expect that customers with time-variant tariffs have some knowledge of the pricing schedule, as they knowingly selected these tariffs. This presents a separate issue, which is the endogeneity, or 'self-selection', of the choice of tariff; specifically, households who select a time-variant tariff may have different consumption patterns which make this tariff favorable to them. We would argue that this is unlikely to be an issue for this estimation, since it is unclear how this would bias elasticity estimates statistically, and it is unlikely that households have enough knowledge to truly optimize tariff selection as such optimization tools are not readily available to customers.

Since there is a linear dependency between price and electricity consumption change, their temporal resolution consists of two data points (active and passive) for each hour of the day and each month of the year - in total 576. To derive a chronological elasticity profile for the entire year, copies of those days are concatenated to represent the full month. Afterwards, the resulting monthly profiles, which consist entirely of copies of the one day are again concatenated to make up a full year. For more details about the average estimated elasticities by hour and month see Table 15. This enables us to multiply the electricity price differences in each hour of the year between two scenarios with the elasticity estimate for these hours, which finally results in an annual electricity demand change profile. The latter can then be used to manipulate the electricity demand profiles in the successive scenario runs. The increased or decreased hourly amount of consumed electricity is assumed not to be compensated in the later course of the year (i.e. no load shift). The change in demand is final. Therefore, applying the elasticities will most probably lead to an overall change in annual household electricity consumption.

Implementation of elasticities in Balmorel

In order to estimate the impact of a potential roll-out of PEAKapp and its associated household electricity price elasticities to the whole of Austria, we utilize the energy modelling framework Balmorel - introduced in Section 3.1. The underlying assumption of the general approach is that an energy system with high shares of variable renewable energy sources and therefore potentially more fluctuating electricity price profiles could benefit economically from an increase in demand side flexibility. To verify this assumption, four different scenarios are calculated – in Stage I of the modelling: I) Business as usual (BAU) and II) a scenario with 100 % renewable energies in 2030 (REN, see Figure 3). Scenarios III and IV are variants of scenario II and calculated in Stage III. Elasticities are applied in the intermediate Stage II. For each of the scenarios, Balmorel provides hourly electricity price profiles that can be compared.

In Stage II, the hourly price differences from the output of Stage I are calculated and multiplied by the hourly elasticity profiles for: 1) The active and 2) the passive PEAKapp users. This operation results in two new profiles, which reflect the relative changes for the household electricity demand profile that were used as an input to the scenario runs of the first Stage.

Stage III of the modelling procedure consists of recalculating the REN scenario with the changed demand profile for both active and passive users. Afterwards, the results of renewable scenarios of the first and third Stage with and without elasticities are compared.

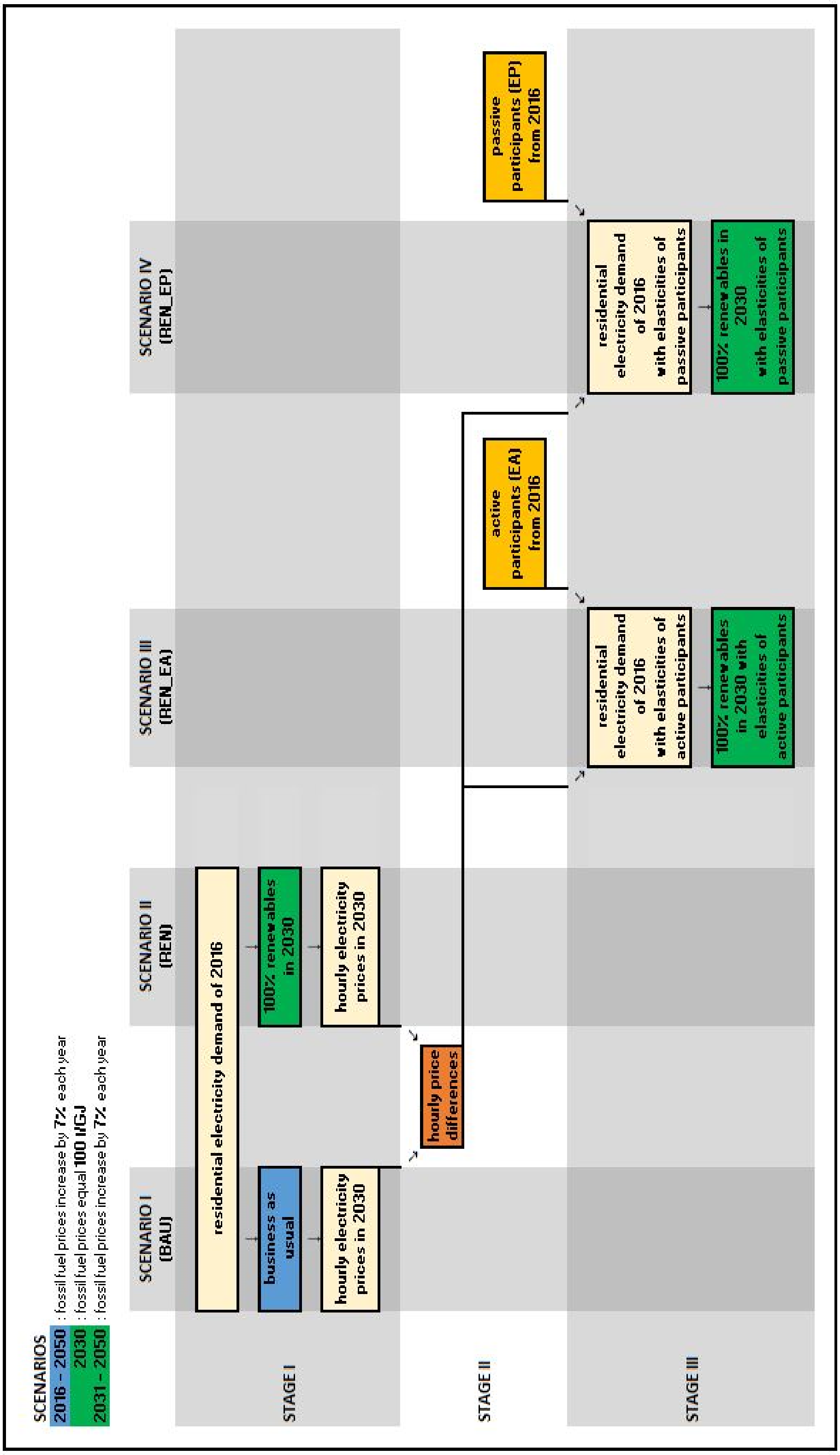

Figure 3: Conceptual illustration of the scenario setup for elasticity implementation using Balmorel

Processing price profiles

Balmorel calculates different electricity price profiles consisting of marginal/wholesale prices for each model time step. Among a number of different factors that can influence these price profiles the setting, whether endogenous investments are allowed for or not, and the different fuel prices in the BAU and REN scenarios showed the biggest impacts. When running the model with endogenous investments, which is the case for BAU and REN, very high price spikes are observed. These spikes correspond to the marginal electricity prices and are thus related to the investment decisions of the solver in these particular time steps. In contrast to the empirical elasticities employed in this research, price spikes are not currently encountered in reality, thus these two time-series need to be harmonized.

In order to do so, all prices greater than the standard deviation of the respective price profile over the year are replaced by the annual average (mean) prices. Logically, the new average prices are much lower than before. This effect is resolved by re-scaling the new price profiles without the peaks, so that the ratio between the annual average prices in BAU (83 € /MWh) and REN (102 € /MWh) in Figure 5 on the left side is the same as the ratio between the ones of REN without peaks (70 € /MWh) and the re-scaled (84 € /MWh) one in Figure 5 on the right. Both have a difference of approximately 20%. For details about the scenario framework see Section 3.4.

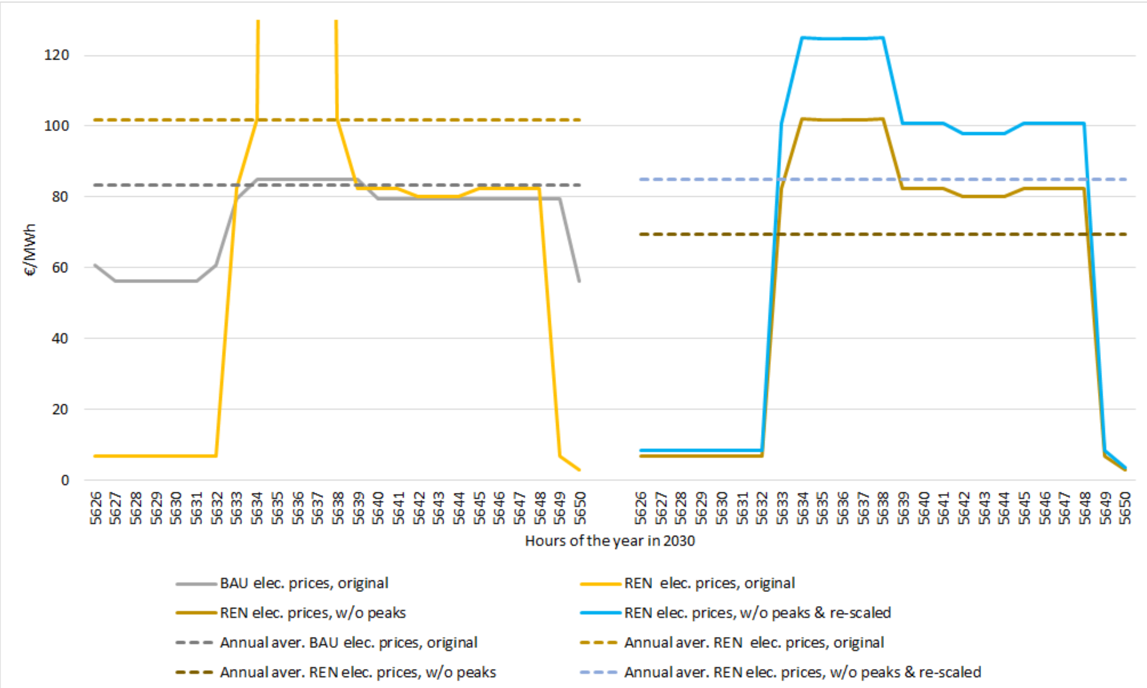

Figure 4: Example of electricity price profiles adjustments in 2030

3.3 Employed data

In this project, Austria was modelled alone as a country which contains one region and two areas (the one with District Heating called AT_DH and one without it called AT_A_NoDH). Inter-connectors were added as net exchange capacities with neighbouring countries: Germany, Italy, Hungary, Switzerland, Czech Republic and Slovenia. The available time slices in Balmorel are years, seasons (as weeks) and terms (as hours). The set for weeks is from S01 to S52 weeks and for hours is from T1 to T168 hours. In order to obtain a high level of precision in the dispatch optimization, the hourly time resolution was adopted for the full year.

Figure 5: Example of electricity price profiles adjustments in 2030

Regarding the input data, the model parameters are incorporated by loading data files. This data forms the basis of parameters and equations in the model. The input data consists among others of energy demand, wind and solar profiles, wind, solar PV and solar heating full load hours, existing and future transmission capacities and generation plants, technical restrictions, technology costs, technology efficiencys and their lifetime, fuel prices, CO_2 taxes.

The employed data is based on multiple sources at the national level: E-control, ENTSO-E, APG, AIT, NETP, Technology Roadmap [20] and Windatlas & Windpotentialstudie Österreich [21]. Below, the main sources used for the most relevant data of the model are stated.

- CO_2 prices:
  The emission policy data used in the model was from E-control [22]. In Figure 6 the CO_2 price development throughout the modelled time horizon is illustrated.
- System capacity:
  The system capacity power data was taken from APG [23] which stands for Austrian Power Grid. The employed data assumed decommissioning of 100% of the technologies capacities when their economic lifetime comes to the end, this has an impact in the existing capacities. Nevertheless, in the model runs, new investments were allowed too.
- Energy demand:
  The source used for the energy demand was ENTSO-E [24], the European Network of Transmission System Operators for Electricity. Load profiles were taken from [25].
- Inter-connectors:
  APG [26] and ENTSO-E[24] were the sources used for the inter-connectors, representing the net exchange capacities between countries.
- Technology data:
  The Austrian Institute of Technology (AIT) [27] provided technology data, which was collected in

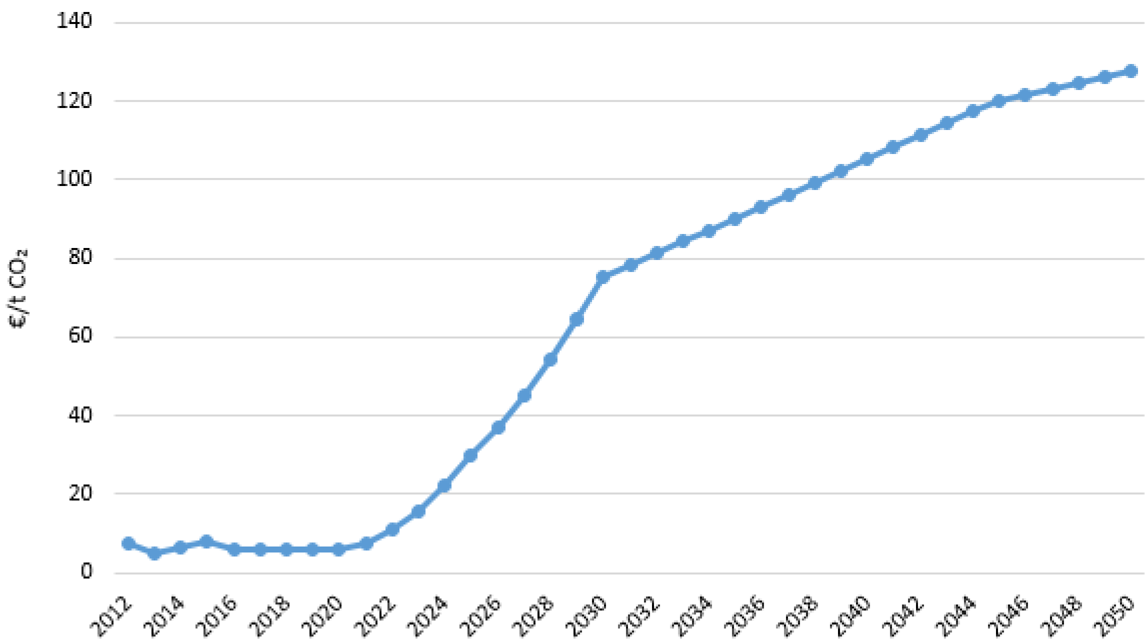

Figure 6: Assumed CO_2 price development in all scenarios [22]

collaboration with TU-Wien from the Austrian private sector.

- Fuel prices:
  Fuel prices were obtained from NETP 2016 (Nordic Energy Technology Perspectives) [28], which was launched by the International Energy Agency and Nordic Energy Research. However, fuel data was collected from the European Environmental Agency [29].

3.4 Scenario framework

This section showcases the four scenario set-ups with their main input data differences by means of two extreme weeks (week nr. 6 and 18) in terms of their residual demands in the base year 2016. Residual demand in our model stands for the electricity demand of all sectors minus the wind production. Week nr. 6, representing a winter week, on the one hand has a very high average residual demand, while week nr. 18, representing a late spring week, on the other has very low one compared to whole year.

Table 5 provides an overview of all four analyzed scenarios. The differences between the two first scenarios without elasticities exclusively rest on increasing fossil fuel prices when going from BAU to REN and is depicted in Figure 7. The differences among the renewable scenarios without and with elasticities (active: REN_EA, passive: REN_EP) rests on varying residential electricity demands due to the adoption of elasticities and is depicted in Figures 8 and 18.

With regard to the method, BAU represents a true descriptive scenario approach. It takes the mainstream assumptions for e.g. fuel costs or technology characteristics into account and describes where this could lead to in the future, if nothing changes, e.g. by policy decisions. In contrast, the three renewable scenarios can be seen as artificial normative scenarios. This is because of the fact that they comply with the Austrian policy decision to de-carbonise the power system by 2030, without having introduced an additional constraint in the model. Instead, to ensure for carbon-neutrality by 2030 in the model, the fossil fuel prices have been increased accordingly. Hence, the REN scenarios use an explorative methodology whilst having a normative sense.

Table 5: Overview of analyzed scenarios, showing main characteristics

scenario	BAU	REN	REN_EA	REN_EP
long name	business as usual	renewable		
description	application of mainstream assumptions	100% renewables in 2030		
method	descriptive	explorative/normative		
elasticities	none	none	active	passive
Stage (in Figure 3)	I	I	III	III

Fuel price development

Figure 7 depicts the fuel fossil fuel price development for BAU (orange) and REN (blue). Obviously, the developments are very different from 2030 onwards. The fossil fuels in the Austrian energy system consist of coal (coal and lignite), oil (heavy fuel oil and fuel oil) and natural gas. In the BAU scenario fossil fuel prices stay at a relatively constant level. The prices in the REN scenario follow the same trend for the first 10 years (2020 to 2030) but then jump to an artificial price of 100€ per gigajoule and then all increase at the same annual rate of approximately 7%. The detailed prices and growth rates are presented in Table 6 for BAU and Table 7 for REN.

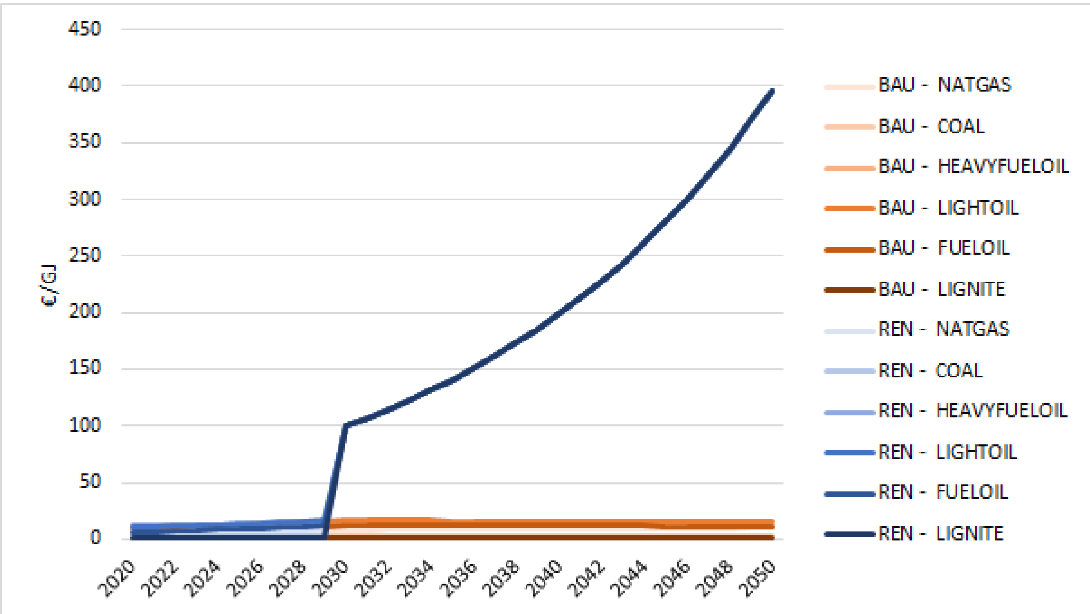

Figure 7: Fuel price development in BAU and REN scenarios based on [28] & own assumptions for REN

Elasticity profiles

In this project, hourly elasticity profiles representing a full year for active and passive PEAKapp users are used to adjust the input residential demand profiles based on the price spreads between BAU and REN. In Figure 8 the profile of week 6 is presented, to see the profile of week 18 go to Figure 18. In both cases, elasticities are mainly below zero as expected, due to the inversely proportional relationship, whereby higher prices incentives lower consumption. Overall, the range goes from 0.1 to -0.6 % change in electricity consumption per % change in electricity price. In general, it can be observed that there is a much higher responsiveness during the day than night as the participants have to actively change their own household consumption based on the price signals distributed via the PEAKapp application. It is also clear to see that active elasticities hold higher reduction potentials than passive ones. Depending on

Table 6: Fuel price development in BAU scenario [28]

	unit	natural gas	coal	lignite	fuel oil	heavy fuel oil	light oil
2020	€ /GJ	5.64	2.31	0.75	5.43	12.60	9.93
aver. annual rate	%	5	2	3	12	0	7
2029	€ /GJ	8.19	2.65	0.99	11.43	12.60	15.94
2030	€ /GJ	8.32	2.67	1.01	12.10	12.60	16.61
aver. annual rate	%	1	0	0	0	0	0
2050	€ /GJ	10.26	2.81	0.96	11.54	12.60	16.05

Table 7: Fuel price development in REN scenario [28] & own assumptions

	unit	natural gas	coal	lignite	fuel oil	heavy fuel oil	light oil
2020	€ /GJ	5.92	2.43	0.79	5.70	13.23	10.43
aver. annual rate	%	5	2	3	12	0	7
2029	€ /GJ	8.60	2.79	1.04	12.00	13.23	16.74
2030	€ /GJ	100	100	100	100	100	100
aver. annual rate	%	7	7	7	7	7	7
2050	€ /GJ	396.07	396.07	396.07	396.07	396.07	396.07

the week, the interval from lowest to highest responsiveness differs, but the overall shape remains similar.

Residential electricity demand

The Figures 9 and 19 of week 6 and 18 respectively serve as references for the full years residential (RESE) electricity demands for each scenario. In this section can be found figures of week 6 and in the Appendix figures of week 18. Week 6 has a high residual load, while week 18 has a relatively low one. BAU and REN without elasticities - both displayed in grey in the following figures - have the same residential demand input profile, while REN with active (REN_EA) in blue and passive (REN_EP) elasticities in orange have two different profiles that were calculated previously in Stage II as described in Section 3.4 with Figure 3. In Figure 9 a clear pattern can be observed throughout the entire week: especially the mid-day peaks are significantly reduced whilst the evening peaks are slightly increased. In total, the consumed energy decreases by applying the elasticities. In contrast to Figure 9, Figure 19 does not depict a clear pattern. Yet, it can be observed that, due to the elasticity profiles of Figures 8 and 18, the change in demand applies exclusively during the daytime hours of the week. Further, the overall electricity demand of the renewable scenarios with elasticities is reduced compared to the REN scenario without elasticities.

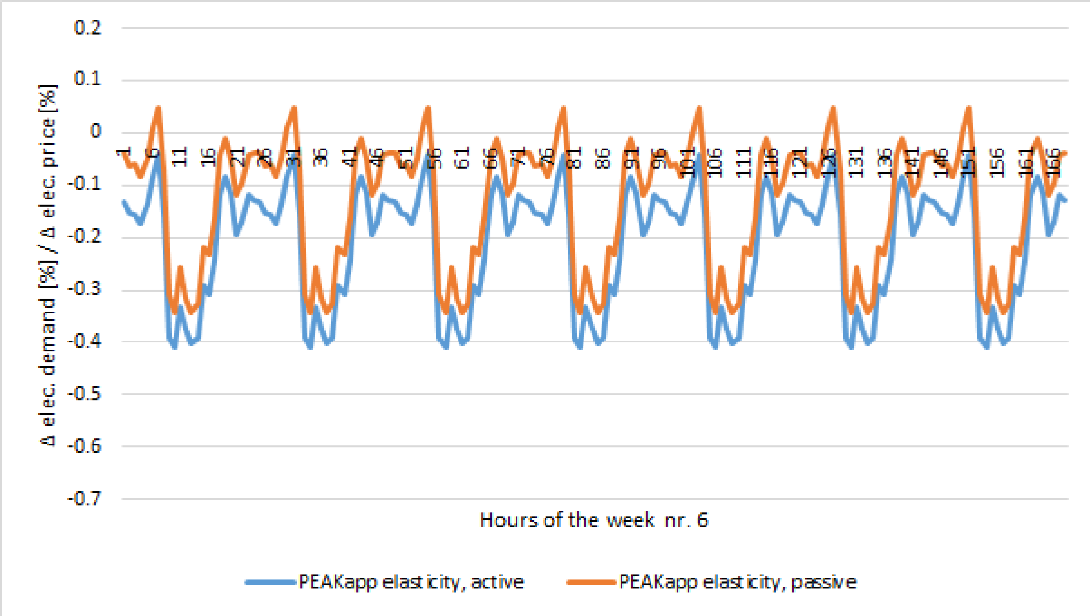

Figure 8: Residential (RESE) elasticity profiles per scenario (week nr. 6), source: own calculation

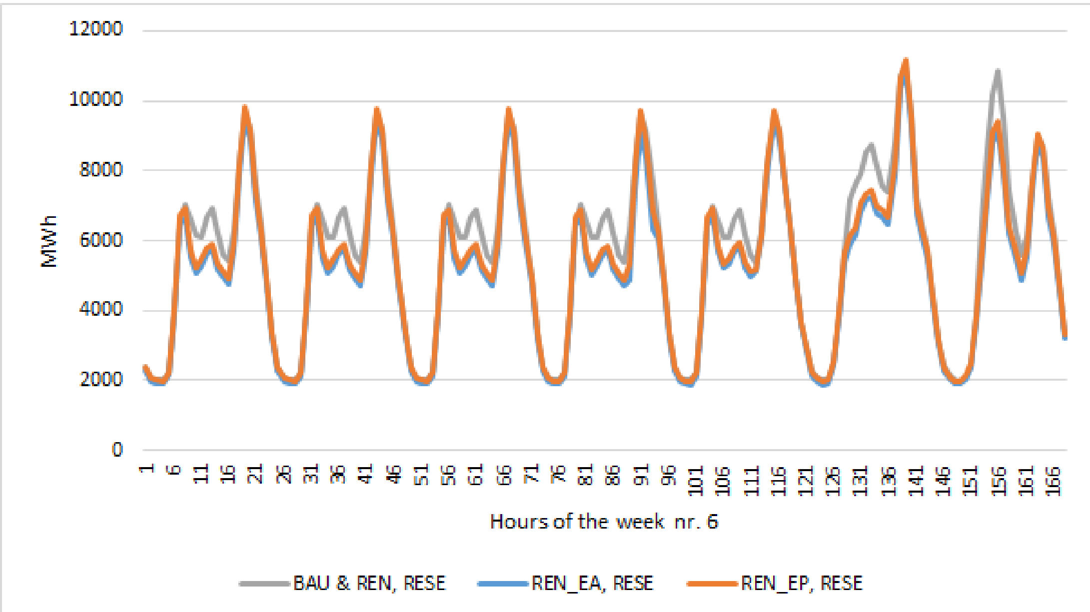

Figure 9: Residential (RESE) electricity demand profiles per scenario (week nr. 6), source: [25] and own calculation

4 Results

This section consists of three main topics: 1) A model validation with regard to the base year 2016 for most data inputs in Section 4.1; 2) scenario comparisons, which focus on electricity prices, capacities, electricity generation by fuel, CO_2 emissions and total system costs in Section 4.2; and 3) sensitivity analyses in Section 4.3 where the sensitiveness of objective values, capacity investments and electricity demands towards changing price/demand elasticities are discussed.

4.1 Model validation

During the model development, attempts were made to ensure a close agreement with real-world data for 2016 in terms of electricity generation, international exchanges and electricity prices. Attention is therefore drawn to each of these in turn by way of a model validation. The process of model development revealed some significant variations in the model results for this base year, which were especially sensitive to assumptions about international cross-border flows. Hence this validation focuses on a comparison of three cases: the real world based on empirical data from [22] called "Historical data", the model of the Austrian system in isolation (with inter-connector capacities and transfers exogenously fixed) called "AT_alone", and the model of Austria connected to Germany, with exogenously fixed inter-connector capacities and endogenous cross-border flows, called "AT&DE".

Firstly, due to the fact that in the base year the existing power plant park is fixed, the focus is on the amount of electricity by fuel and technology in this year. Figure 10 shows the generation by fuel type and generally illustrates a close agreement between all three cases, especially for coal, hydro-power, solar energy and wind. There is substantially more deviations between these three cases for the generation from wood-chips, due to its fuel price. The largest discrepancy is encountered for gas-fired electricity generation, which is around 16 TWh in the AT & DE case, compared to about 7-8 TWh in the other two cases. Therefore, the case with high net export of electricity has the highest use of natural gas, this is due to its fuel price and technology efficiency. Thus, the results show that there is a big influence in the exported electricity

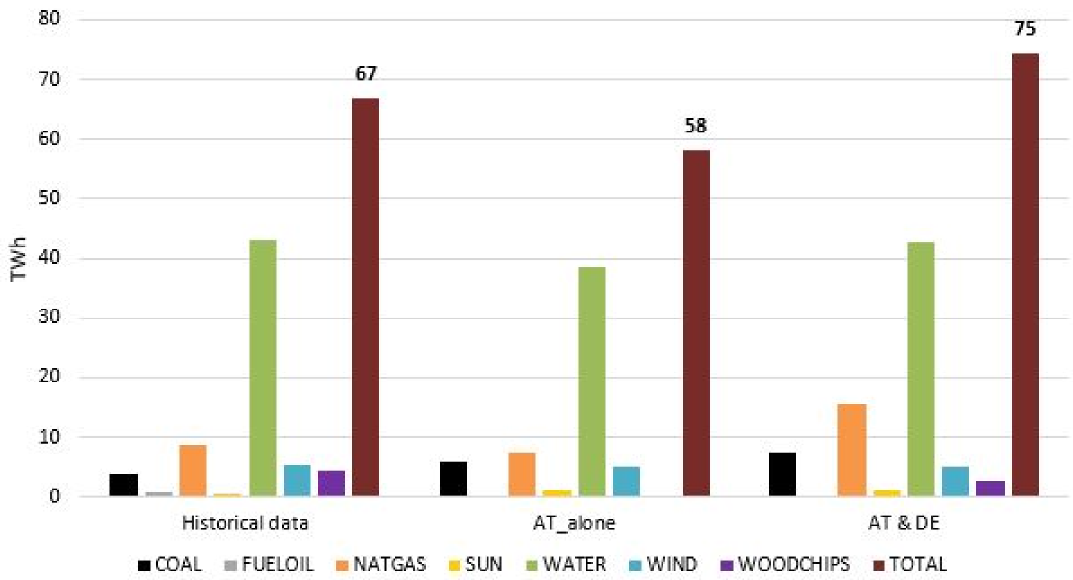

Figure 10: Validation of model results: electricity generation by fuel in 2016 for three cases, historical data case source [22]

Historical data shows that there have been significant imports of electricity to Austria from Germany, 7

TWh net in 2016, cf. Table 8. This is reflected in the case with AT_alone, in which there is a net import of 8 TWh, due to the cross-border flows being fixed. In the AT&DE case, however, there is a net export of around 12 TWh to Germany, due to the much lower electricity prices in Austria compared to Germany.

Table 8: Transmission flow with neighbouring countries in 2016, [TWh]

cases	Historical data	AT_alone	AT&DE
export +	19	15	13
import −	26	23	1
net	−7	−8	12

Finally, the mean annual marginal electricity prices shown in Table 9, depict that the Historical data and AT&DE cases have very similar values, with 29 and 27 €/MWh respectively. There is a strong deviation in the case with Austria alone, however, with a mean annual price of about 12 €/MWh.

Overall, then, there is a closer match of the real generation mix and the cross-border flows in the AT_alone case, which are exogenously fixed. In this case the prices are very low due to the avoidance of imported (more expensive) electricity from Germany. On the other hand, the AT&DE case has much more realistic prices but higher overall generation and significant electricity exports. It was therefore decided to adopt the AT_alone case for the remainder of this analysis, as the lower electricity prices can be put down to two potential reasons. The first is the lack of costs for the cross-border flows within the Balmorel model, and the second is the fact that sunk costs, in terms of existing power plants, are not considered. Existing power plants already stand and can generate, but are not necessarily already amortized. Both of these factors would tend to increase the electricity prices in the model and push them closer to those encountered in the real world setting. Further model validation is therefore left for further work and is picked up again in the discussion in Section 5.3.

Table 9: Mean annual marginal electricity prices in 2016, [€/MWh]

cases	Historical data	AT_alone	AT&DE
mean annual electricity prices	29	12	27

4.2 Scenario comparison

This section is dedicated to presenting and comparing the different scenarios explained in Section 3.4 for 2030. It includes for each scenario the electricity demands and price profiles, exogenous and endogenous investments in generation capacities and the corresponding fuel consumption, emissions of CO_2 and total system costs.

Electricity demand

Figure 11 depicts the electricity demand profile of the different scenarios throughout the year. On the one hand, the BAU and REN scenarios were executed with the blue profile, which is without elasticities. On the other hand, the REN_EA and REN_EP demands were calculated with the elasticities, obtaining the orange and purple profiles respectively.

Overall the BAU and REN scenarios have a higher and smoother demand than REN_EA and REN_EP scenarios. However, the scenarios with elasticities show some peaks throughout the year. Those peaks mainly come from hours where the difference in electricity prices between the BAU and REN scenarios

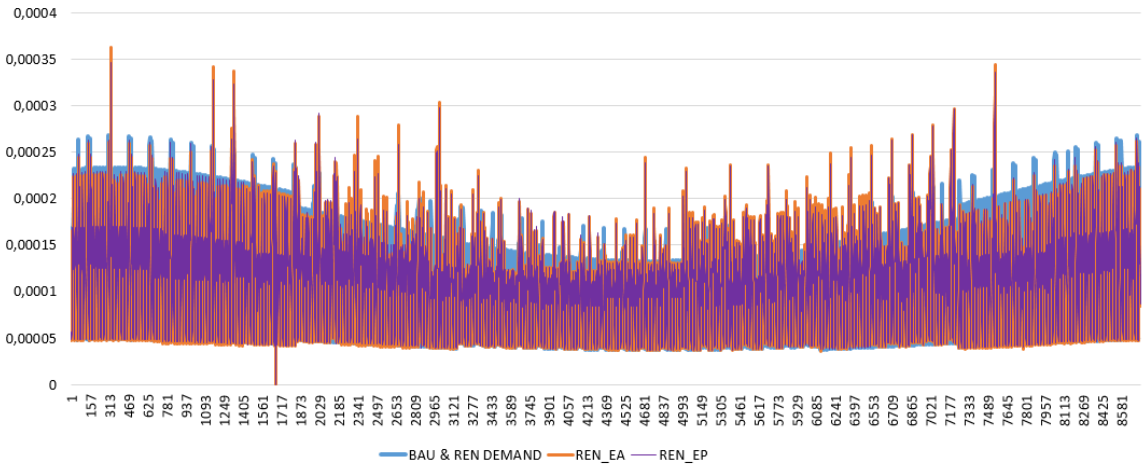

Figure 11: Annual electricity demand profile for all four scenarios

is significant. The higher price difference in these periods results in a demand change that impacts the overall demand curve, producing new peaks that stand out from the remainder of the profile.

Electricity prices

The comparison of electricity price curves in 2030 is performed only for the scenarios BAU and REN as they are utilized to derive new demand profiles for REN_EA and REN_EP. For details about the approach see Figure 3. The electricity prices are given hourly in € /MWh, representing the marginal values shown in Figure 12 and allowing for endogenous capacity investments.

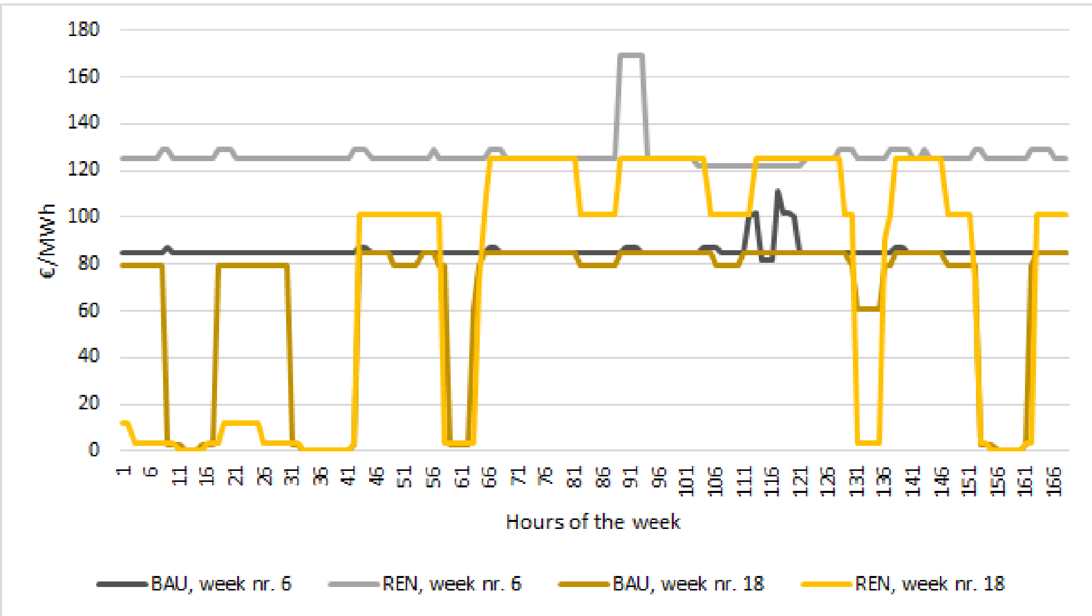

Figure 12: Electricity price profiles of week nr. 6 & 18 in 2030

Depending on the electricity demand and availability of variable renewable energy sources, the profiles have quite different shapes. In times of relatively low demand and/or high penetration of renewable energy production the electricity prices are decreasing and vice versa. The profiles of week 6 as in Figure 12 have high residual demands and hence relatively low renewable electricity production. Therefore, constant high prices with few peaks can be observed. In contrast, the profiles of week 18 in the same figure have low residual demands due to high shares of renewable production compared to the demand. This results in a more fluctuating profiles with lower average prices as depicted in Table 10. For the sorted electricity price profiles of all scenarios, with and without elasticities see Figure 20 in the Appendix.

Table 10: Electricity price statistics for weeks nr. 6 & 18 in 2030 and scenarios BAU & REN, [€ /MWh]

week nr.	6		18	
scenario	BAU	REN	BAU	REN
maximum	111	170	85	125
mean	86	126	65	72
minimum	82	122	0	0

Capacities

Figure 21 in the Appendix shows electricity generation capacity investments. The BAU scenario has the lowest investments in electric storage (4 GW), solar PV (13 GW) and wind turbines (0,5 GW), but is the only scenario with combined heat and power (CHP-extraction) capacity investments (1 GW), since the fossil fuel prices are almost kept constant in this scenario. All of the renewable scenarios have similar capacity investments. The REN scenario has the highest capacity investments in condensing technologies since it does not have high peaks in electricity demand and it has more base load than the other renewable scenarios with elasticities, which are REN_EA and REN_EP. Regarding the scenarios with elasticities, it seems that REN_EA, which is the scenario with the highest elasticities, is the scenario with the highest investments in electric storage, solar PV and wind turbine capacities. The main reason for this is because the REN_EA scenario has higher peaks in demand than REN_EP, thus it needs more renewable capacity and storage to cover the demand. With regards to the total electricity generation capacity investments, scenarios with elasticities have more total investments than scenarios without elasticities, even though scenarios with elasticities have lower net electricity demand than BAU and REN. However, the high peaks in electricity demand represented in Figure 11 depict the need for high capacities in some hours. These peaks are supplied by renewable technologies as solar PV, wind turbines and electric storage.

Figure 13: Exogenously and endogenously installed electricity generation capacities in 2030.

Figure 13 illustrates the electricity generation capacities in the system in 2030. The exogenous capacities represent the existing capacities, which are decommissioned throughout the plant's operating lifetime (for more details see Section 3.1), and the endogenous capacities represent the new capacity investments as Figure 21 presents. The energy system of the renewable scenarios relies on the use of storage and hydro power in order to supply the electricity peak demand in periods with a lower penetration of wind and solar.

Electricity generation by fuel

The REN scenario has the highest total electricity generation, followed by the REN_EP and REN_EA scenarios respectively. The BAU scenario has the lowest total electricity generation even though the electricity generation by natural gas, hydro and coal is higher than in the remaining scenarios, mainly because the amount of electricity that comes from wind, electric storage and wood-chips is much lower. In the Appendix, more details about the electricity generation by fuel in each scenario are illustrated in Figure 22 .

With regard to the renewable scenarios, Figure 14 displays the comparison of the electricity generation by fuel between the scenarios with elasticities to the renewable scenario without elasticities. In REN_EA and REN_EP wind turbines and electric storage are used up to 5-8% more than in the renewable scenario without elasticities. This increased utilization is expected to be used in the electricity demand peaks as laid out in Figure 11.

The REN scenario has lower total installed capacity but higher total electricity generation than REN_EA and REN_EP. Mainly, the biggest difference comes from the electricity generated by wood-chips, in REN is produced around 2 TWh more than in the REN_EA and REN_EP scenarios.

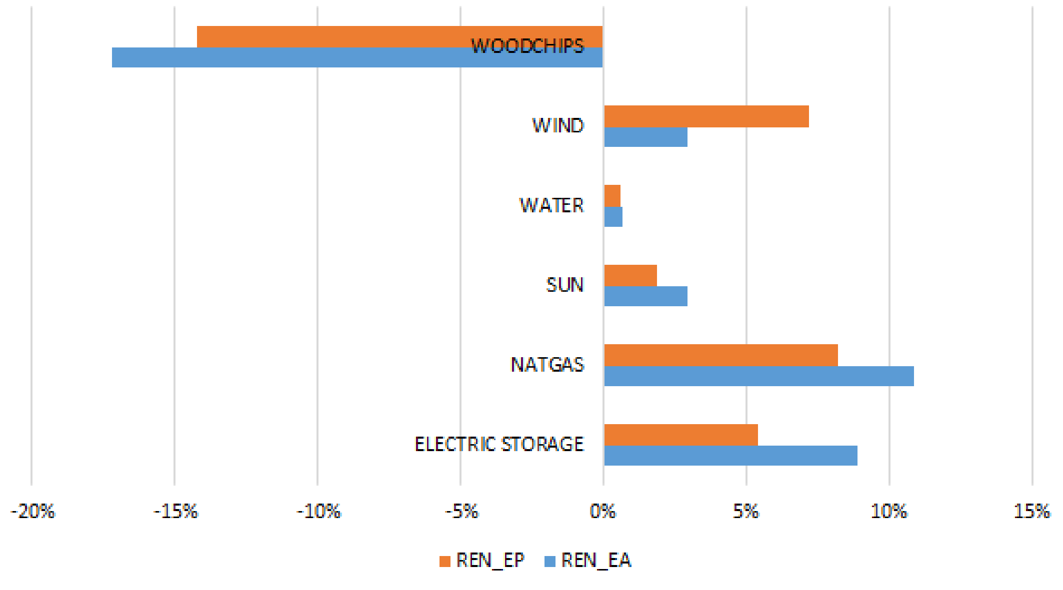

Figure 14: Comparison of REN_EA and REN_EP annual electricity generation by fuel to REN in 2030

In the BAU scenario the electricity generated by coal is very significant (92 GWh) compare to the renewable scenarios. Among the renewable scenarios, REN_EA and REN_EP produce 3 GWh more compared to REN. A similar trend is followed by natural gas. More electricity is generated by coal and natural gas in some peak hours when it is cheaper overall to deploy already existing technologies rather than building new condensing capacities that would then run on wood-chips.

Emissions

Annual CO_2 emissions are presented in Table 11. The annual CO_2 emissions of the renewable scenarios were reduced by 97% compared to BAU. This effect is explained by the increase in fossil fuel prices from 2030 in the renewable scenarios. For more details see Tables 6 and 7.

Table 11: Annual CO_2 emissions in 2030, [kton]

fuel	BAU	REN	REN_EA	REN_EP
coal	86.27	1.12	3.21	3.18
fuel oil	0.04			
natural Gas	5610.21	147.78	163.75	159.85
total	5696.51	148.90	166.96	163.03

Table 11 provides a detailed overview of all scenarios' annual CO_2 emissions. The annual emissions in the scenarios with elasticities (see the REN_EA and REN_EP scenarios) are higher than in the REN scenario due to the specific fuels deployed in each scenario. The higher consumption of coal and especially natural gas for flexibility in the scenarios with elasticities result in higher annual CO_2 emissions. For more details see Figure 14.

Total system cost

One of the most relevant results of an optimization model is the objective function, which gives the total discounted system cost for the complete time horizon. It should be emphasized here that, due to significant uncertainties in the modelling approach (discussed in Sections 3.4, 5.2 and 5.3), the absolute value of the objective function is not shown. Instead we concentrate on the relative changes in this value compared to the BAU scenario, as this should give an indication of the scope to reduce these system costs through a more flexible residential demand side.

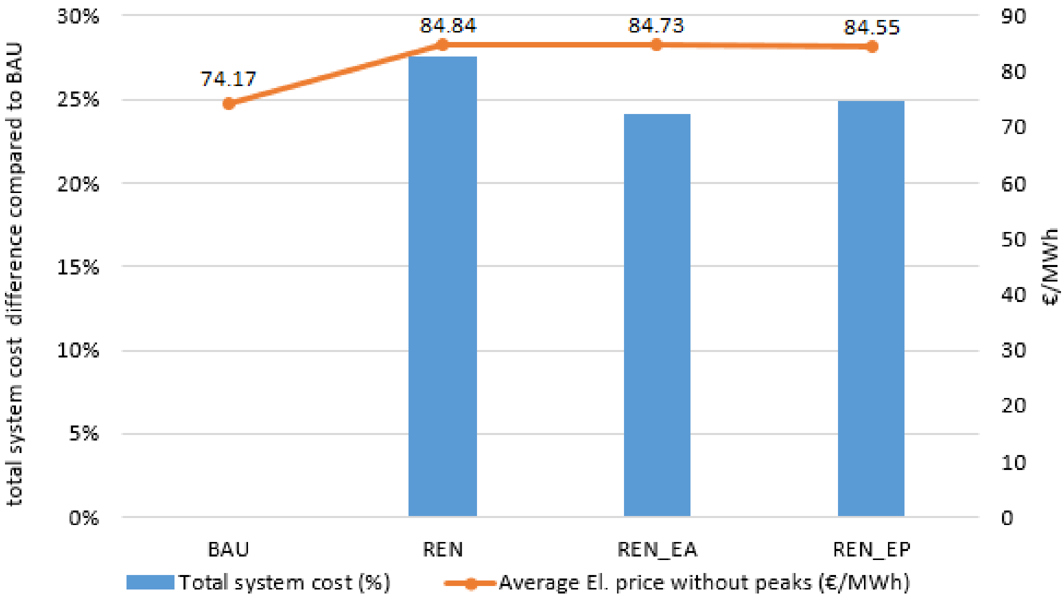

Figure 15: Total system cost, % difference compared to BAU & average electricity prices in 2030.

In order to get a better overview, Figure 15 illustrates the total system cost % difference compared to the BAU scenario as a reference, here the effect of the elasticities can be appreciated. The impact of the elasticities on the system is even higher in the REN_EA scenario than in the REN_EP scenario. The total system cost increases by 24%, 24.6% and 27.6% in the REN_EA, REN_EP and REN scenarios respectively compared to the BAU scenario. The higher the impact of the elasticities, the lower the total system cost. Therefore, results show that the elasticities have a positive influence on the total system cost by decreasing it 2.6% in REN_EA and 2% in REN_EP compared to REN. However, the average marginal electricity prices do not have a significant variation among the renewable scenarios. In the REN_EA and REN_EP scenarios the average marginal electricity price decreases by 0.1% and 0.3% respectively compared to the REN scenario.

Figure 16 provides information about the most relevant cost categories of the total system cost of REN_EA and REN_EP compared to REN. The capital cost reflects the new capacity investments. The REN scenario has the highest capital cost due to investments in condensing technologies. Comparing the scenarios with elasticities, REN_EP has higher capital costs since it is investing more in wind power and less in electric batteries than REN_EA, so the latter has the lowest investment.

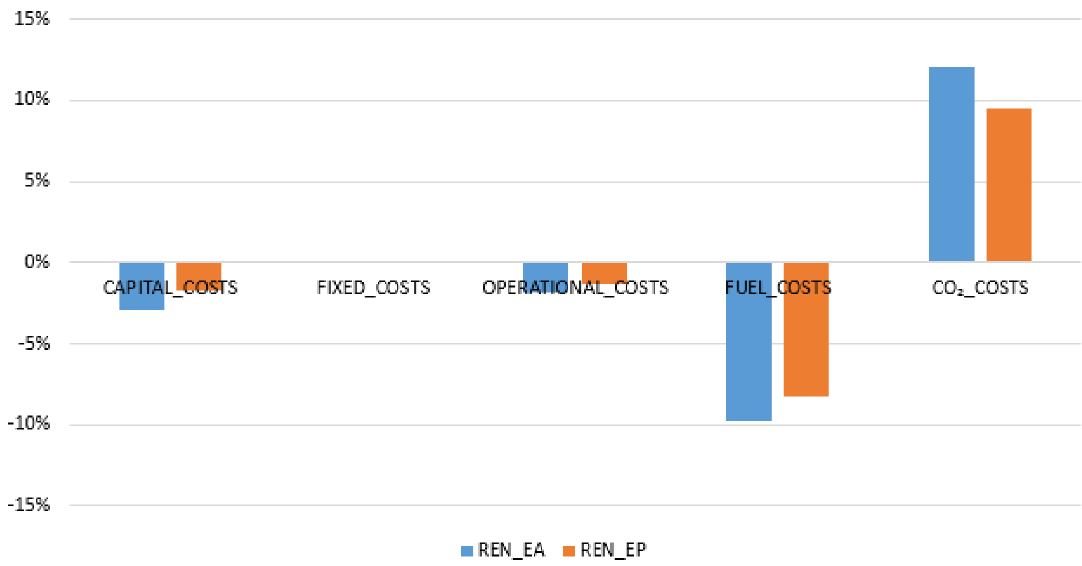

Figure 16: Difference in total system costs per category for REN_EA and REN_EP scenarios compared to REN in 2030

The operational costs (O&M) represent the variable operation and maintenance cost. They follow the same trend as the capital cost since the only electricity technologies with O&M costs are condensing technologies and wind turbines. The fuel costs correspond to the fuel use in each scenario. In Table 12 the total fuel use in the energy system is represented.

Table 12: Total fuel use in the energy system in 2030 [TWh]

scenario	BAU	REN	REN_EA	REN_EP
value	104	121	115	116

Comparing the renewable scenarios there is a significant reduction in the fuel costs when the elasticities are implemented in the system due to less fuel used. On the other hand, the CO_2 costs are higher in the scenarios with elasticities since they follow the annual CO_2 emission's results, which are detailed in Table 11. Hence since the fossil fuel prices are the same for the renewable scenarios, the fuel cost directly corresponds to the fuel use and the CO_2 cost is associated with the specific fuel use in each scenario.

4.3 Sensitivity analysis

In order to get a better understanding of the model's behaviour towards the introduction of elasticities, we investigated the following results with regard to their sensitivity to change: 1) objective values; 2) total investments in electricity capacity; 3) total annual electricity demand profiles. In the course of this analysis, the elasticity profiles are multiplied by factors from 0.5 (-50%) to 1.5 (+50%) in steps of 0.1. With the resulting elasticity profiles, new demand profiles are derived as input to the REN_EA and REN_EP scenarios. Thus, the following figures consist of only these two scenarios. The sensitivity analysis comes with a change in the modelling perspective from a normative sense with a focus on CO_2 reduction to an explorative one that focuses more on the effects of different magnitudes of elasticities. The target of the normative approach, which is the reduction of CO_2 emissions in the renewable scenarios, is already reached.

As shown in the following Figure 17 (orange and brown lines), the relation between elasticity and objective value change is linear and inversely proportional. However, the total impact seems rather small and there is no threshold rate identifiable. Basically, it describes well the expected effect: the greater the elasticities, the lower the objective value, because of an overall improved residential electricity demand profile by shape and energy consumption. An increase of this specific elasticity type therefore holds potential for positive socio-economic effects in terms of cost savings at the total system level.

An ascending, rather flat s-shape can be recognized for the total capacity investments. In comparison to the objective value, the impact is relatively large and the trend is directly proportional. So an increase in the magnitude of the elasticities employed here implies an increase in investments in new capacities. Further, a threshold rate sets in at $\pm$ 40% for both scenarios – generally speaking, REN_EP reaches the threshold slightly earlier. This implies that greater elasticities lead to greater investments into new electricity generation capacity until the thresholds are reached. Then the effect seems to abate, meaning that the additional investments are sufficient to cope with increasing elasticities. In our case, more elasticities entail lower total system costs by means of increasing investments into PV and battery capacity at relatively low costs. This can be explained by the fact that the elasticities can also lead to increased demand peaks in hours where the prices as well as the demands are at high levels and that the they only take effect during day time hours. Therefore, an overall benefit for the system can prevail.

The relation between changing elasticities and total electricity demands follows a strong linear, inversely proportional trend. Again, the impact of the change stays relatively small and it does not show a threshold at any point. Overall, it is very similar to what we see for the objective values. It simply illustrates, that the greater the elasticity effect, the lower electricity demand remains in the input data. Thus, their shapes can serve as an appropriate proxy for the additional amount of electricity that can potentially be saved due to change in elasticities and vice versa.

Overall, the results and trends of this analysis are as expected regarding the objective values and electricity demands, however with a relatively small impact. The sensitivity of the total capacity investments depicts slightly different results with a reversed trend compared to the other two.

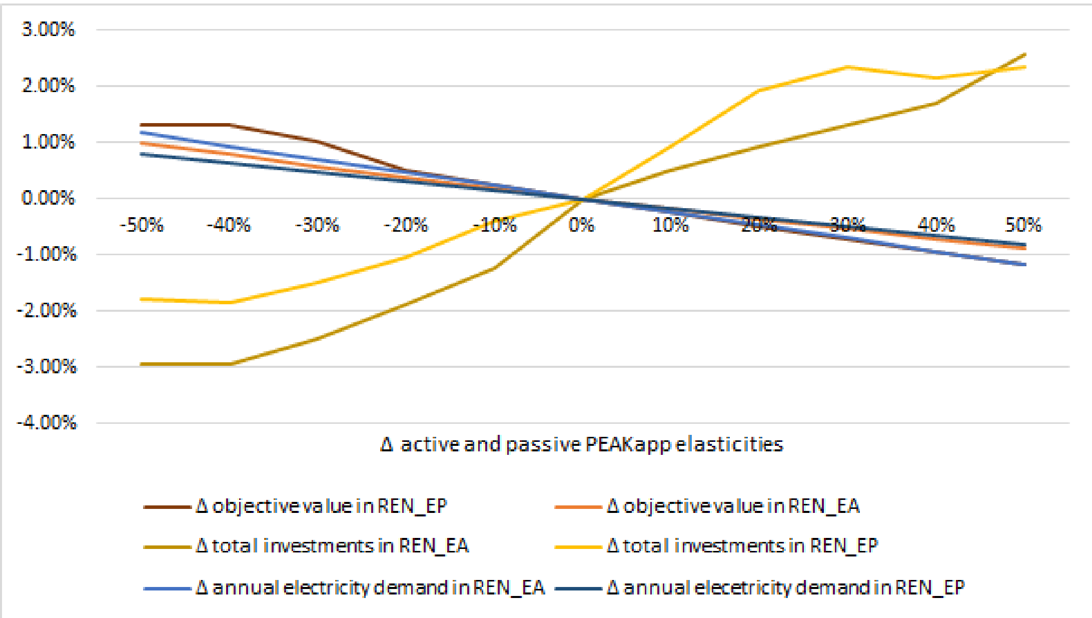

Figure 17: Sensitivity of the objective values, total capacity investments and electricity demand towards active and passive elasticity changes

5 Discussion

This section consists of three main parts: 1) Section 5.1 includes a discussion of results obtained for 2030, 2) a discussion of the employed methodology follows in Section 5.2 and 3) suggestions of future work are presented in Section 5.3.

5.1 Discussion of results

The results are based on the application of the Balmorel model within a scenario framework, reflecting the plans of the Austrian government compared to a business as usual development, to reach carbon neutrality in the electricity sector by 2030. We chose this approach as it seems most realistic. Four scenarios were studied, BAU and REN without elasticities and REN_EA and REN_EP with elasticities. In this section an overview of the results and how they have met the initial expectations is provided. Then, the main results among these scenarios are discussed: generation capacities, electricity prices, CO_2 emissions and total system cost.

The results braodly meet the initial expectations, showing that the implementation of elasticities in the electricity system provide lower fuel use, lower demands, higher investments in renewable technologies and lower total system costs. As for the REN_EA scenario, which has the highest elasticities, it represents the scenario with lowest fuel use, highest generation capacity investments and the lowest total system cost among the renewable scenarios. However, elasticities do not have such a big impact on the electricity prices.

The renewable scenarios reduce the annual CO_2 emissions by approximately 97% compared to the BAU scenario. This important reduction is due to the high fossil fuel prices assumed in 2030, which bind the model to use renewable technologies in order to reach the Austrian government goal of 100% renewable in electricity generation by 2030. However, an important finding was that the scenarios with elasticities have higher annual CO_2 emissions than the REN scenario, this result was due to a higher utilization of natural gas and coal in the scenarios with elasticities. As explained in section 3.4, it was not the intention to reduce the CO_2 emissions also for the REN scenarios with elasticities, but to investigate the effects of the latter.

In summary, the economic system benefits increase with higher elasticities, but this comes with a slightly negative impact on the environmental performance, due to different fuel utilizations. This is different to other studies, e.g. Li and Pye (2018)[1]. We estimate a reduction in total system costs by 2,6% in the REN_EA and 2% in the REN_EP compared to REN. These can be considered to represent the higher end of the scale. Another study employing the Balmorel model and an add-in to consider the techno-economic characteristics of load shifting potentials (see Section 5.3 below) found similar results for the Nordic and Baltic region. Although they do not explicitly derive price elasticities, the authors identify a peak downshift of between 1% and 7% excluding and including electrical heating applications respectively [30].

When looking into the different price components, electricity prices obtained in the scenarios with elasticities are slightly lower than in the one without. Regarding the differences between the REN_EA and REN_EP scenarios, there was no large effect on the electricity price. Even though, we rate the general modelling framework as adequate, the strong similarity between the two elasticity groups as described in Section 3.2 were unexpected and are further discussed in the next Section 5.2.

Overall, the general trends in the results are in the expected direction, but their magnitude is very small. The consideration of price elasticities of electricity demand increases the flexibility of the energy system, as represented in the Balmorel model, but only by a small amount in terms of overall system costs and electricity prices. This could be due to several reasons, as explored in the next section.

5.2 Discussion of methodology

The model validation in section 4.1 as well as the sensitivity analysis in section 4.3 indicate that the developed Balmorel model is a reasonable representation of the Austrian power and district heating sectors. Whilst there were some small deviations in the model outputs from expectations or historical data, these are considered to be minor in the context of this analysis. Especially the lower electricity prices encountered in the Austrian system are thought to be due to overlooking both cross-border flow costs and sunk costs of existing power plants. The focus in this work is on analyzing relative effects of assumption changes in a scenario framework, hence absolute results are secondary.

The largest effect comes from the introduction of the elasticities in the first place, rather than through the two subgroups, active users (REN_EA) and passive users (REN_EP). Whilst there is a difference in the results between these two groups, these differences are very minor in comparison to those between scenarios with and without elasticities. E.g. the total system costs as shown in Figure 15 are only 0.6% different between the REN_EA and REN_EP scenarios, while REN and REN_EA are separated by more than a four times this, 2.6%. This could relate to the definition of these two subgroups, whereby one group had access to the app (active) and the other did not (passive). In fact, some participants had access to the app without using or installing it, so that they might be wrongly classified as active. Further work is required in order to ascertain whether significantly different elasticities result from a different definition of the two groups. For example, if subgroups of users that are heavily engaged with the app had a stronger response to price signals.

The PEAKapp sample includes about 1600 households in Upper Austria, mostly owner-occupiers with high levels of disposable income, as evidenced by the ownership of saunas (20%) and jacuzzis (26%). The implicit assumption in this work is that this sample is representative for the whole of the Austrian residential sector, which is almost certainly not the case. Some analysis of the sample and comparison with the national population in the residential sector support this assumption. It revealed, that the households in the sample have on average: 1) 24% more residents; 2) 39% larger living areas; 3) 63% more often their own properties. See Appendix 1.1 for the detailed statistics.

Hence the sample under-represents lower income groups, living in rented accommodation with smaller dwellings and fewer appliances. From the literature, we know that these groups' potential to be flexible is constrained by their overall lower demand and smaller capital stock of appliances. Furthermore, unrelated to the representativeness of the PEAKapp sample, we also implicitly assume that (in the REN_EA scenario) all of the households are active users of PEAKapp. This is clearly an upper bound for the likely penetration of these apps in the near future and therefore represents a technical potential rate, whilst also overlooking the associated costs of a widespread rollout.

In addition, the modelling approach and scenario framework also has its weaknesses. Firstly, the focus in this work is on the flexibility of demand through active consumer participation, but there are strong synergies between these measures and others in the broader context of renewable energy integration. Examples include but are not limited to energy storage, supply-side-flexibility, network expansion and densification, sector coupling and flexibility in other demand sectors. By focusing on the residential sector we intentionally analyze the system-level impacts of demand-side flexibility here, but also neglect such flexibilities in other, large demand sectors such as industry and services. Secondly, the employed approach adopts a central planner perspective assuming complete centralized decision-making and control over the energy system. In reality, of course, investment decisions about new power plants involve various stakeholders with different decision criteria. More importantly, the exploitation of widespread demand side flexibility, in this case throughout the Austrian residential sector, would require an equally widespread availability of technical infrastructure (e.g. smart meters, smart appliances) and market frameworks. Whilst the former is at an advanced stage in Austria, the latter does not yet enable real time/dynamic pricing to all customers. Thirdly, the employed approach does not take into account the strong current reductions in the costs of batteries and the associated trends in households to invest in stationary storage and/or electric vehicles. As these costs reduce further in the future, emerging niches such as prosumers optimizing their own supply and consumption, and regional energy markets, could drastically impact the energy system and invalidate such a centralized perspective like the one taken in this work.

Regarding some of the limitations of the energy system model, there are three issues that would have contributed to producing more realistic results. The first is the fact that the heat side was not very detailed since the main focus of this analysis was on the electricity side. It could have been better represented, for example by adding more heat areas (small, medium and large). Especially by increasing the spatial resolution of the developed model and including individual district heating areas and their associated heat and power plants, the behaviour as outlined in Section 4.1 would be improved. More specifically, the existing capacities of generation of heat and electricity plants could be more accurately measured and therefore the generation of heat and power by fuel and technology improved. However, this relies on more detailed data about district heating areas and heat and power plants, which is one of the reasons this was already challenging with just one DH area. The second issue is that the modelled years were 2030 and 2035 due to high computational time issues, but it could have been an interesting approach to model more years and with longer time horizon to see the effects in 2040 and 2050. Thirdly, all simulations were performed without allowing for new investments in transmission lines with neighbouring countries. It was preferred to keep the inter-connectors as a fixed parameter and optimize Austria alone. However, it could have helped to reduce the capacity investments if the model was executed with all the neighbouring countries as part of the model too and allow for new transmission investments. Finally, only one scenario for a highly renewable future Austrian energy supply system was considered, but obviously many potential configurations are conceivable.

There are also some limitations relating to the general methodological framework employed and shown in Figure 3 above. Firstly, the employed elasticities represent point elasticities and are not necessarily valid for large price gaps. In other words, these point elasticities are assumed to be linear functions, which apply throughout the whole range of analysed price and demand. In reality, though, these elasticity functions would not necessarily be linear, especially at the extremes of demand where a marginal change is more significant than in "mid-load" regions. Secondly, these elasticities are short term, in the sense that they were derived from a field trial that measured the short term behaviour of households. But they are employed in this context as both short and long term elasticities to represent how household load profiles could respond to short term price changes in the short and long term. In the longer term context, such as the several decades analysed here, one would expect an adaptation of the demand side in response to longer term changes in prices - for example by households adapting their technology portfolio in the context of changing external factors. This implies that our results are the lower bound of the actual behavioural change that would occur if people were made more aware of dynamic electricity prices. In addition, the model assumptions are taken from different years: the model base year (including demand curve) is 2016, the elasticities stem from the field trial in 2018, and both of these sources are used for future years such as 2030.

5.3 Further work

As discussed above, there are several areas in which the employed methodology could be improved in order to reduce the uncertainty associated with the results and these are briefly summarized in this section.

Firstly, an alternative Balmorel modelling framework involves exploiting detailed bottom-up data on the potentials and costs of load-shifting measures. This approach requires a differentiation of the demand down to the appliance level, as well as between flexible and non-flexible portions. In an energy system modelling context the costs of shifting this flexible load is also required. None of this data was available in the present case for Austrian households but one possibility would be to develop bottom-up models based on time-use data/diaries which generate load profiles for household appliances, which are themselves classified into flexible and non-flexible devices. Costs for load shifting could then be taken from the literature and/or based on results of field trials of dynamic tariffs.

Secondly, another approach to analysing the flexibility of the residential demand side would involve detailed bottom-up simulations of the load profiles. In order to derive an estimate for technical potentials for flexibility in this sector, we could utilize the Austrian time of use survey data (TUD). This would give us a better understanding about structure of the electricity demand. By differentiating between flexible and non-flexible appliances, the demand could be split into two fractions and cost estimates for load shifting derived from the literature, the technically possible elasticities of several different household archetypes and temporal resolutions. The processing of the TUD can be performed e.g. by the stochastic CREST [31] simulation model, which has already been extended to Germany [32]. The output would represent a technical upper limit as well as associated costs for demand side flexibility, which could be used as an input, either for the employed Balmorel modelling framework or the alternative one mentioned in the paragraph above with an add-in.

Thirdly, the analyzed subgroups within the PEAKapp Austrian field trial could be newly defined. The differentiation employed within this work simply distinguishes between those households with the app and those without. But it does not account for the fact that some households had the app without using it, whereas others were intensive users. In order to better account for this observed effect, alternative subgroups could be analysed. For example, price elasticities between groups of PEAKapp and non PEAKapp users could be compared, for example by focussing on heavy users of PEAKapp, or those that were actively shown price-related information via the PEAKapp discount message functionality. Such enhancements to the methodology might alter the observed differences between the active (REN_EA) and passive (REN_EP) scenarios reported here.

Finally, the Balmorel model should have a better representation of the heat side in Austria, this can be improved by introducing more areas (large, medium or small areas). Regarding the studied sectors in the model, further work could involve modelling more sectors to see their environmental performance based on a change in the electricity production. Hence this would consider all sectors and potentials for flexibility there and measure the impact of the implementation of the elasticities in the energy system.

6 Summary and conclusions

This report has assessed the extent of the positive effects of the PEAKapp in the context of a widespread application of the ICT to Human ecosystem. Two field trials were carried out in the project, which involved a large-scale roll-out of the PEAKapp alongside control groups in Austria and Estonia. In this Deliverable we focused on the Austria field study, which involved around 1600 participants over a period of about 18 months. The thorough analysis of the field trial data was carried out by JKU, DTU and Tecnalia and is documented in Deliverable D.4.1. One aspect of this analysis involved deriving short-term price elasticities for the households participating in the trial. These elasticities are employed within this report in order to analyze the responsiveness of households to future changes in electricity prices under different framework conditions. To this end we employ the energy system framework Balmorel that allows a comparative static analysis of the electricity market equilibrium, assuming different aggregated consumption profiles under alternative pricing regimes. The overall objective thereby is to analyse the economic benefits to the whole Austrian energy system of utilizing residential demand side flexibilities at the national scale. More specifically, the objective is to analyze the impact on economic, technical and environmental indicators of a widespread exploitation of demand side flexibility.

The method employs the existing linear optimization energy system model Balmorel, which is extended to cover Austria in the given context. It thereby employs the price elasticities mentioned above as an exogenous input to derive changes in an exogenous demand in the residential sector. The analysis is carried out for the timeframe to 2030 within a scenario framework of four scenarios. These include a BAU and REN, in both of which the demand is assumed to be inelastic. Two additional variants of the renewable scenario consider these elasticities and therefore have flexible demands, whereby we distinguish between active and passive flexibilities. Active implies load shifting on behalf of the participant, and in this context means having the PEAKapp and using it. Passive on the other hand means either not having the PEAKapp, or having it but not using it. By comparing these four scenarios in terms of diverse economic, technical and environmental criteria, we are able to explore the system level impact of PEAKapp in Austria. The novelty of the method lies in the approach to consider the flexible demand as well as the application to the Austrian energy system. The findings show that the elasticities can potentially lower fuel consumption and electricity demands, promote investments in renewable technologies and lower total system costs when striving for a carbon-neutral power system.

Overall, the results broadly conform to expectations. The impact of the flexible residential demand side (e.g. on the system cost) in the system context is small but significant. In combination with other measures to integrate renewable energy technologies, this flexibility will need to play a crucial role. One surprising finding was the very small deviation between the results in the scenarios with active and passive PEAKapp users. Whilst the scenario with active app users exhibited some slightly lower total system costs, this relative difference was marginal compared to the renewable scenario without flexible demand. In other words, the total system cost increases by 24%, 24.6% and 27.6% in the REN_EA, REN_EP and REN scenarios respectively compared to the BAU scenario. Hence further attention should be paid to some particular aspects of the method, for example the segmentation of the sample into active and passive groups will be revisited. The system-level impacts reported here should be interpreted as technical upper limits, due to the inherend bias in the employed field trial sample and the fact that point elasticities to assess short and long term demand responses. In addition, the representativeness of the sample is clearly a limitation, so that additional data, perhaps also from the Estonian field trial should be employed to duplicate this approach in another context. The method could also be enhanced to account for more detailed estimates of the cost-potential for flexibility, based on empirical studies and/or bottom-up simulation tools. All of these aspects will be the focus of future work.

References

[1] Pye S. Li, P. H. Assessing the benefits of demand-side flexibility in residential and transport sectors from an integrated energy systems perspective. Applied Energy . 228:965–979, 2018. doi: https://doi.org/10.1016/j.apenergy.2018.06.153.

[2] W. Matar. A look at the response of households to time-of-use electricity pricing in Saudi Arabia and its impact on the wider economy. Energy Strategy Reviews. 16:13–23, 2017. doi: https://doi.org/10.1016/j.esr.2017.02.002.

[3] Balyk O. Hevia-Koch P. Katz, J. The impact of residential demand response on the costs of a fossil-free system reserve. ENERDAY 2016 - 11th Conference on Energy Economics and Technology. 2016. URL https://tu-dresden.de/bu/wirtschaft/ee2/ressourcen/dateien/lehrstuhlseiten/ordner_enerday/ordner_pacp/ordner_fpap/full_papers_2016/KATZ-Full_Paper.pdf.

[4] Bramstoft R. Koduvere H.-Pizarro Alonso A. Balyk O. Kirkerud J. G. Ravn H. Wiese, F. Balmorel open source energy system model. Energy Strategy Reviews, Assessing the benefits. 20:26–34, 2018. doi: https://doi.org/10.1016/j.esr.2018.01.003.

[5] Alahivl A. Malik F.-Humayun M. Safdarian A. Lehtonen M. Ali, M. A market-oriented hierarchical framework for residential demand response. International Journal of Electrical Power and Energy Systems. 69:257 – 263, 2015. doi: https://doi.org/10.1016/j.ijepes.2015.01.020.

[6] Blumberga D. Blumberga A.- Rosa M. Laicane, I. Reducing Household Electricity Consumption through Demand Side Management: The Role of Home Appliance Scheduling and Peak Load Reduction. Energy Procedia. 72:222–229, 2015. doi: https://doi.org/10.1016/j.egypro.2015.06.032.

[7] Klavs G. Grohnheit, P. E. Elastic electricity and heat demand in the Balmorel model. Second International Conference: Simulation, Gaming, Training and Business Process Reengineering in Operations, September 8-9 2000, Riga Technical University, Riga, Latvia. 2000.

[8] Togeby M. Hindsberger-M. Pedersen T. E. Jensen, S. G. Valuation of Demand Response in the Nordic Power Market. Paper presented at Demand Response in Australia - Delivering on the Potential, 16 November 2006, Melbourne, Australia. 2006. URL http://www.ieadsm.org.

[9] Bolkesj T. F.- Ilieva I. Tveten, . G. Increased demand-side flexibility: market effects and impacts on variable renewable energy integration. International Journal of Sustainable Energy Planning and Management. 11:33–50, 2016. doi: https://doi.org/10.5278/ijsepm.2016.11.4.

[10] Koduvere H. Palu D. I. Kuhi-Thalfeldt D. R. Rosin D. A. Mishra, S. Assessing Demand Side Flexibility with Renewable Energy Resources. 2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC). 2016. URL https://www.ieee-pes.org.

[11] Andersen F. M. Morthorst P. E. Katz, J. Load-shift incentives for household demand response: Evaluation of hourly dynamic pricing and rebate schemes in a wind-based electricity system. Energy. 115:1602–1616, 2016. doi: https://doi.org/10.1016/j.energy.2016.07.084.

[12] Hans Ravn. The Balmorel Model Structure. 03(2.12 Alpha):132, 2001. doi: 10.5281/zenodo.823692. URL http://balmorel.com/images/downloads/model/BMS303-20190311.pdf.

[13] Hardi Koduvere Amalia Pizarro Alonso Olexandr Balyk Jon Gustav Kirkerud Åsa Grytli Tveten Torjus Folsland Bolkesj Marie Mnster Hans Ravn Frauke Wiese, Rasmus Bramstoft. Energy Strategy Reviews: Balmorel open source energy system model. 20:26–34, 2018. doi: https://doi.org/10.7249/R366.

[14] GAMS Development Corporation. GAMS solver manuals. URL https://www.gams.com/latest/docs/S_CPLEX.html#CPLEXlpmethod.

[15] Energy System Analysis Models. URL http://www.esymodels.man.dtu.dk/balmorel.

[16] George Bernard Dantzig. Linear Programming and Extensions, the RAND Corporation. (R-366-PR): 641, 1963. doi: https://doi.org/10.1016/j.esr.2018.01.003. URL https://www.rand.org/pubs/reports/R366.html.

[17] Steve Martin and Nicholas Rivers. Information provision, market incentives, and household electricity consumption: Evidence from a large-scale field deployment. *Journal of the Association of Environmental and Resource Economists*, 5(1):207 – 231, 2018. URL https://EconPapers.repec.org/RePEc:ucp:jaerec:doi:10.1086/694036.

[18] Ben Gilbert and Joshua Graff Zivin. Dynamic salience with intermittent billing: Evidence from smart electricity meters. *Journal of Economic Behavior & Organization*, 107(PA):176–190, 2014. doi: 10.1016/j.jebo.2014.03.01. URL https://ideas.repec.org/a/eee/jeborg/v107y2014ipap176-190.html.

[19] Katrina Jessoe and David Rapson. Knowledge is (less) power: Experimental evidence from residential energy use. *American Economic Review*, 104(4):1417–38, April 2014. doi: 10.1257/aer.104.4.1417. URL http://www.aeaweb.org/articles?id=10.1257/aer.104.4.1417.

[20] International Energy Agency. Technology Roadmap. page 48, 2010. URL https://www.pvaustria.at/wp-content/uploads/2013/07/Roadmap-IEA.pdf.

[21] Windatlas. URL https://www.windatlas.at/downloads/Follow_Up_Bericht_2014.pdf.

[22] E-control Database. URL https://www.e-control.at/documents/.

[23] Austrian Power Grid, . URL https://www.apg.at/en.

[24] ENTSO-E (European Network of Transmission System Operators - Electricity) Transparency Platform Database. URL https://www.entsoe.eu/data/transparency-platform/.

[25] Synthetische Lastprofile. URL https://www.apcs.at/de/clearing/technisches-clearing/lastprofile.

[26] Austrian Power Grid and Transmission, . URL https://www.apg.at/en/markt/Markttransparenz/Uebertragung/NTC-Prognosen.

[27] Hamid A. Demet, S. Austrian Institute of Technology. Unpublished. 2019.

[28] NETP2016-Nordic Energy Technology Perspectives. URL https://www.nordicenergy.org/project/nordic-energy-technology-perspectives/.

[29] European Environmental Agency. URL https://www.eionet.europa.eu.

[30] Torjus F. BOLKESJO Jon G. KIRKERUD, Niels O. NAGEL. The Role of Demand Response in the Future Renewable Northern European Energy System. Unpublished. 2019.

[31] Loughborough University. CREST model. URL https://www.lboro.ac.uk/research/crest/demand-model/.

[32] Kleinebrahm M. Yunusov T. Lorincz M. J. Torriti J. McKenna, R. Exploring socioeconomic and temporal characteristics of British and German residential energy demand. 2018.

Appendices

1 Appendix

1.1 Tables

category	description	AT_{all}*	PEAKapp sample	difference [%]
number of households (hhs)	total	3890000	1571	-99.96
number of residents	mean/hh	2.22	2.76	+24.32
square meters	mean/hh	99.6	138.1	+38.66
home owned	mean/hh	47.8	0.78	+63.18
dryer	mean/hh	0.33	0.589	+78.48
swimming pool	mean/hh	not specified	0.264	-
sauna	mean/hh	not specified	0.205	-

Table 13: Comparison of selected statistical indicators between the entire Austrian residential sector and the PEAKapp participants. *Based on: https://www.statistik.at/web_de/statistiken/menschen_und_gesellschaft/wohnen/index.html

Table 14: Electricity price statistics for 2030 and all scenarios, [€ /MWh]

scenario	BAU	REN	REN_EA	REN_EP
maximum	111	172	179	188
mean	74.17	84.84	84.73	84.55
minimum	0	0	0	0

	Sample Average	January	February	March	April	May	June	July	August	September	October	November	December
Average Elasticity	-0.142**	-0.129*	-0.153*	-0.138	-0.144*	-0.202***	-0.183***	-0.198***	-0.193***	-0.132*	-0.119*	-0.179**	-0.113*
Midnight - 1am	-0.0572	-0.0789	-0.101	-0.0818	-0.0874	-0.0799	-0.0771	-0.0597	-0.0888	-0.0136	-0.0478	-0.0863	-0.0659
1 - 2am	-0.0401	-0.0421	-0.119	-0.0613	-0.0743	-0.0671	-0.0338	-0.0275	-0.0523	-0.0221	-0.0421	-0.0863	-0.0391
2 - 3am	-0.0394	-0.0465	-0.124	-0.0773	-0.0451	-0.0644	-0.0319	-0.0281	-0.0809	-0.0200	-0.0238	-0.0954	-0.0540
3 - 4am	-0.0518	-0.0775	-0.141	-0.101	-0.0533	-0.0870	-0.0353	-0.0296	-0.0778	-0.0153	-0.0422	-0.144	-0.0760
4 - 5am	-0.0274	-0.0632	-0.108	-0.0972	-0.0459	-0.0410	-0.0198	-0.0265	-0.0433	0.0145	-0.0136	-0.117	-0.0721
5 - 6am	0.0269	0.00981	-0.0513	-0.0757	-0.0120	-0.0557	-0.0271	0.0273	0.00812	0.0917	0.0701	0.00548	0.0225
6 - 7am	-0.0498	0.0273	-0.0158	-0.0201	-0.0896	-0.225**	-0.154	-0.143	-0.118	-0.0423	0.0338	-0.0320	-0.0340
7 - 8am	-0.155**	-0.0599	-0.131	-0.174*	-0.239***	-0.270***	-0.207**	-0.244***	-0.194**	-0.162*	-0.107	-0.186**	-0.0895
8 - 9am	-0.229***	-0.322***	-0.355***	-0.343***	-0.241***	-0.258***	-0.213**	-0.278***	-0.253***	-0.217**	-0.303***	-0.422***	-0.283***
9 - 10am	-0.428***	-0.450***	-0.384***	-0.406***	-0.401***	-0.457***	-0.401***	-0.475***	-0.474***	-0.413***	-0.411***	-0.480***	-0.407***
10 - 11am	-0.384***	-0.369***	-0.296***	-0.291**	-0.306***	-0.456***	-0.371***	-0.486***	-0.520***	-0.428***	-0.335***	-0.369***	-0.375***
11am - 12pm	-0.409***	-0.365***	-0.352***	-0.314**	-0.340***	-0.439***	-0.385***	-0.524***	-0.519***	-0.469***	-0.372***	-0.462***	-0.376***
12 - 1pm	-0.422***	-0.427***	-0.383***	-0.357***	-0.273**	-0.460***	-0.454***	-0.542***	-0.522***	-0.423***	-0.373***	-0.482***	-0.418***
1 - 2pm	-0.390***	-0.353***	-0.366***	-0.310***	-0.297***	-0.421***	-0.466***	-0.510***	-0.495***	-0.358***	-0.345***	-0.454***	-0.337***
2 - 3pm	-0.289***	-0.245**	-0.269**	-0.226**	-0.253**	-0.322***	-0.323***	-0.399***	-0.379***	-0.307***	-0.285***	-0.288***	-0.210**
3 - 4pm	-0.268***	-0.277***	-0.282***	-0.266**	-0.251**	-0.292***	-0.336***	-0.343***	-0.341***	-0.251**	-0.276***	-0.304***	-0.184**
4 - 5pm	-0.304***	-0.235**	-0.216**	-0.295***	-0.300***	-0.347***	-0.431***	-0.465***	-0.438***	-0.317***	-0.240**	-0.227**	-0.169**
5 - 6pm	-0.236***	-0.178*	-0.0797	-0.105	-0.293***	-0.364***	-0.385***	-0.362***	-0.374***	-0.274**	-0.196**	-0.236**	-0.158*
6 - 7pm	-0.186**	-0.142	-0.0606	-0.0594	-0.282**	-0.379***	-0.373***	-0.415***	-0.374***	-0.246**	-0.153	-0.195**	-0.113
7 - 8pm	-0.146*	-0.104	-0.0841	-0.0844	-0.149	-0.255***	-0.216**	-0.263***	-0.253***	-0.156*	-0.132	-0.186**	-0.0619
8 - 9pm	-0.150**	-0.131*	-0.168**	-0.125	-0.0646	-0.170*	-0.128	-0.208**	-0.191**	-0.121	-0.0659	-0.202**	-0.0793
9 -10pm	-0.132*	-0.126	-0.147*	-0.120	-0.125	-0.161*	-0.169**	-0.179**	-0.124	-0.135	-0.131*	-0.188**	-0.0835
10 - 11pm	-0.0823	-0.0620	-0.0903	-0.0600	-0.0740	-0.143	-0.185**	-0.164*	-0.128	-0.122	-0.115	-0.150	-0.0633
11pm - Midnight	-0.0925	-0.102	-0.0987	-0.0596	-0.0935	-0.124	-0.142	-0.118	-0.124	-0.0630	-0.0580	-0.118	-0.0721

* significant at $\alpha = 10\%$, ** significant at $\alpha = 5\%$, *** significant at $\alpha = 1\%$

Table 15: Average Estimated Elasticities by hour and month

1.2 Figures

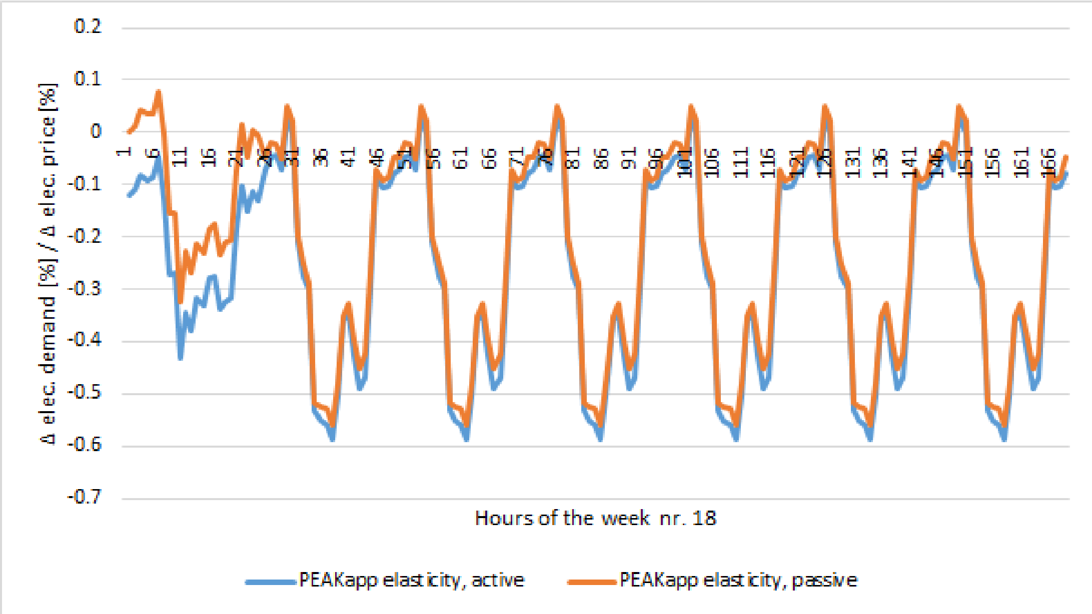

Figure 18: Residential (RESE) elasticity profiles per scenario (week nr. 18), source: own calculation

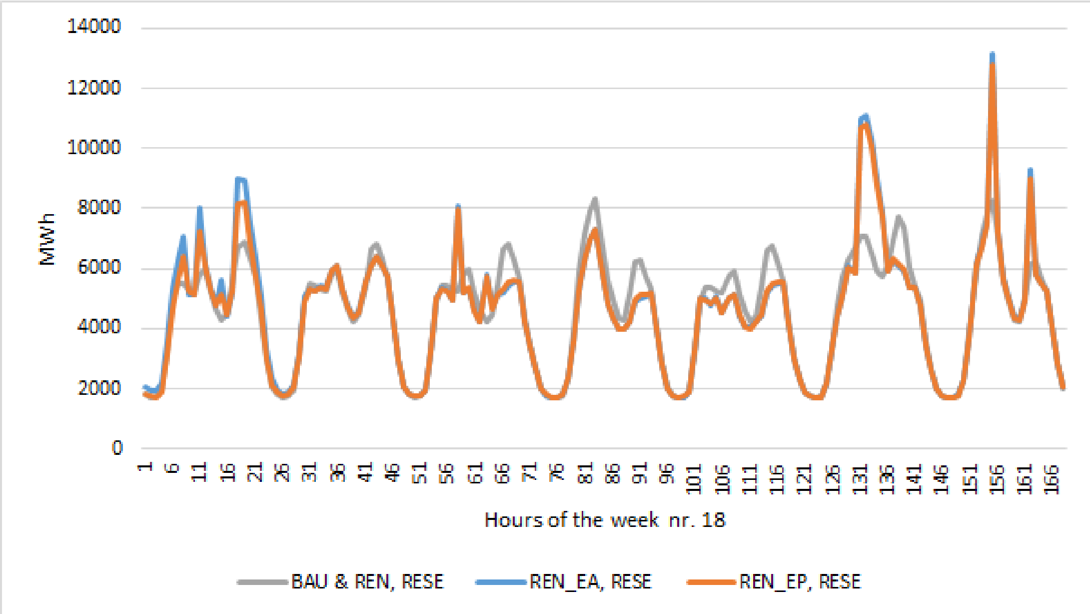

Figure 19: Residential (RESE) electricity demand profiles per scenario (week nr. 18) [25] and own calculation

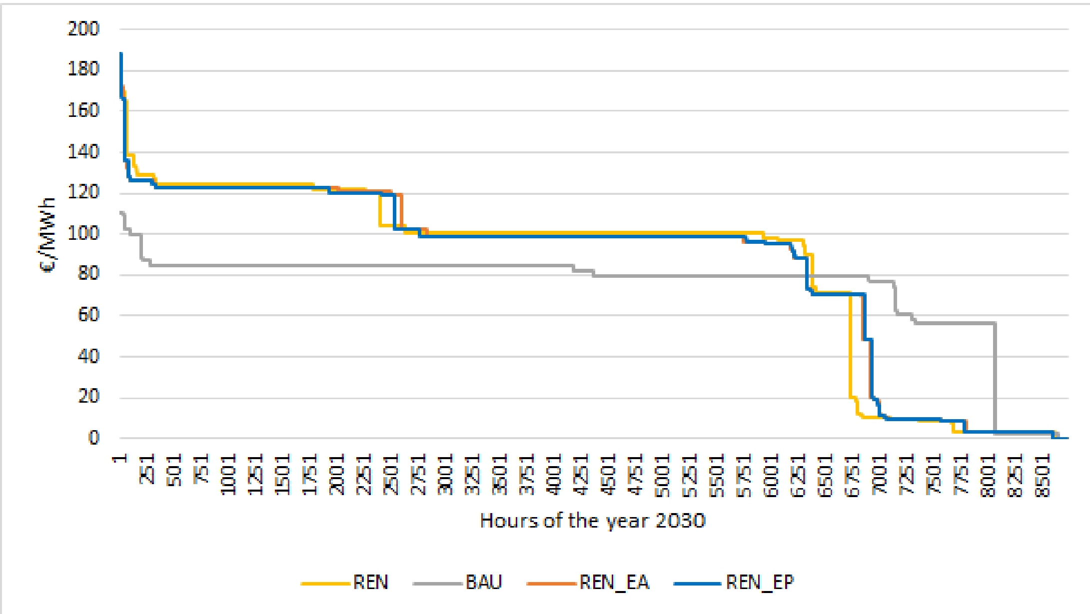

Figure 20: Sorted electricity price profiles for the full year and each scenario

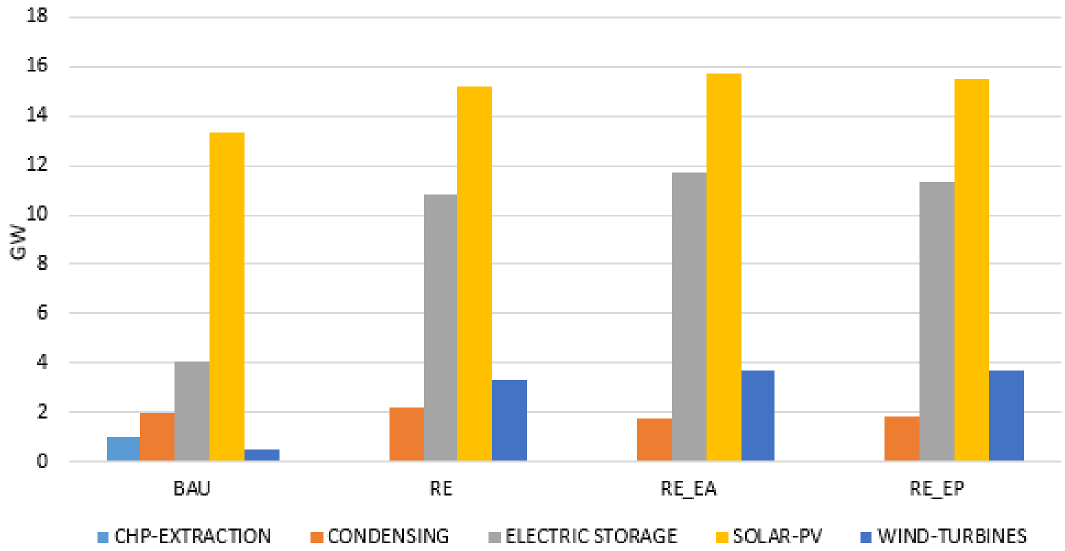

Figure 21: Endogenous electricity generation capacity investments in 2030

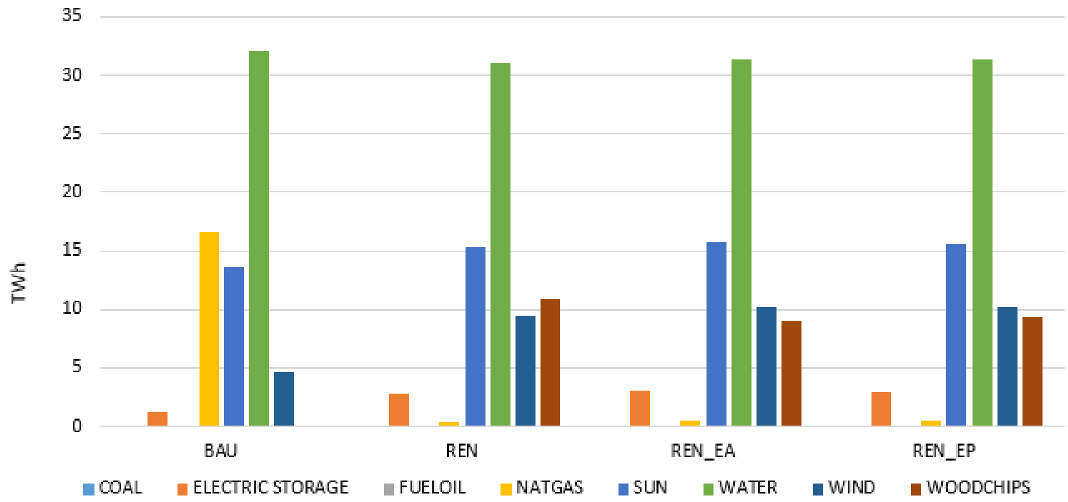

Figure 22: Electricity generation by fuel in 2030